Development of an Effective Semantic Knowledge Base for IoT in Agriculture

Thesis submitted in partial fulfilment of the requirements for the degree of

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COMPUTER SCIENCE

BY

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CERTIFICATE

On the basis of declaration submitted by **Ms. P Salma Khatoon**, student of Ph.D, I hereby certify that the thesis titled **"Development of an Effective Semantic knowledge Base for IoT in Agriculture"** which is submitted to the Department of Computer Science & Information Technology, School of Technology, Maulana Azad National Urdu University (A Central University), Gachibowli, Hyderabad, India in Partial fulfilment of the requirement for the award of the degree of Doctor of Philosophy, is an original contribution with existing knowledge and faithful record of research carried by her under my guidance and supervision.

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DECLARATION

I, **P Salma Khatoon**, solemnly declare that the research leading to this Ph.D. thesis on **Development of an Effective Semantic knowledge Base for IoT in Agriculture** is my original work. The study has been conducted at the Department of Computer Science & Information Technology, School of Technology, Maulana Azad National Urdu University (A Central University), Hyderabad. It is further declared that to the best of my knowledge and belief, it has not been submitted earlier for the award of any other research work.

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ABSTRACT

IoT Semantic interoperability in agriculture refers to the ability of different IoT devices and systems to work together seamlessly, allowing farmers to easily integrate new technologies into their operations and have meaningful communications. This can include everything from sensors that monitor soil moisture and crop health to drones that survey fields and tractors equipped with GPS and automation systems. By having interoperable systems, farmers can easily access and analyze data from multiple sources, which can help them make more informed decisions about planting, harvesting, and managing their crops. Additionally, semantic interoperability can also help farmers reduce costs by allowing them to use equipment from multiple vendors rather than being locked into a single proprietary system. Overall, IoT Semantic interoperability in agriculture is essential for creating a more efficient and sustainable agricultural industry.

A collection of technologies and standards known together as the semantic web are what make it possible for robots to comprehend the significance of the content found on the internet. Semantic web technologies can be used in the context of agriculture to improve data management and decision-making by making it simpler to share, access, and comprehend data related to crops, weather, soil conditions, and other factors that affect agricultural production. This is accomplished by making it possible to more easily share, access, and understand data.

In the field of agriculture, one of the primary applications of the semantic web is to improve the interoperability and integration of data. It is possible to connect data from many sources by using semantic web technologies. These technologies make use of common vocabularies and ontologies, which enables computers to comprehend the relationship between the data and draw conclusions based on it. This may provide farmers the ability to acquire and examine data from a variety of sources, such as weather predictions, satellite imaging, and sensor data, which can assist them in making better educated choices about the planting, harvesting, and management of their crops. Semantic web technologies also enable the creation of a knowledge-based systems for agriculture. It allows farmers to access a wealth of information about

agricultural practices, crop management, pest control, and disease control from multiple sources and make it more easily accessible and understandable. Additionally, semantic web technologies can be used to create intelligent systems that can automatically analyse data and make predictions about crop yields, water usage, and other factors that affect agricultural production.

Because it offers a standardized language for defining and connecting material on the web, RDF (Resource Description Framework) is an essential piece of technology for the semantic web. It is essential because it helps machines to comprehend the significance of the facts as well as the connections among them, and it facilitates the integration of data and the interoperability of various computer systems. In RDF, which is a way of defining information, a triple consists of three components: a subject, a predicate, and an object. A subject, a predicate, and an object make up a triple. The triples can be linked together to create a network of interconnected data, which can be used to represent complex information and relationships.

The fundamental purpose of this research is to provide a semantic knowledge base for agricultural Internet of Things devices. This knowledge base will provide solutions for crop selection, crop monitoring, and yield prediction, all of which will assist farmers at various stages of crop production in achieving higher yields. A web interface has been created that provides the user with access to the developed frameworks. This work presents a Crop Selection model, which takes the inputs from the farmers, such as soil type, climate conditions, available resources etc., and suggests the best suitable crop for the given conditions.

The Internet of Things (IoT) already connects a broad range of different devices, including sensors, microcontrollers, actuators, as well as smart devices like mobile phones, smart watches, and other similar items. In the framework of data gathering, the Internet of Things makes a substantial contribution to the generation of data. This is true in many different industries, including medicine, agriculture, the military, and many others. Because both the Internet of Things (IoT) but also online semantics offer fertile ground for a broad range of possible applications, a significant number of research teams have been urged to concentrate their efforts on the intersection of these two domains. Because of this, it is now feasible to gather data and exert transparent control over a variety of items. Utilizing all of this heterogeneous data effectively is a major challenge. By satisfying certain data needs in the Internet of Things industry, ontologies provide a solution to this issue that has been plaguing the industry. This work presents an interoperability framework using Temperature, Humidity, Moisture, pH and Light intensity sensors. The purpose of this work is the improvement of a dynamic agricultural ontology, which can be updated depending on the requirements of the user. It provides a semantic knowledge base for the IoT devices used in Agriculture that enables the devices and applications to share the common knowledge across the domain, which will ensure semantic interoperability in agricultural IoT. The developed ontology framework allows the user-defined ontologies to be accepted and offer an interface for the online update of owl files.

The technology of the Internet of Things may also be utilised to forecast crop yields and inform farmers about the best time to plant or harvest a crop. For example, using data from weather forecasts and soil moisture sensors, an IoT based system can predict the best time for planting or harvesting. Farmers are able to make choices about crop selection and management that are better informed when they have access to data and insights that are updated in real time. This, in turn, may assist to enhance crop yields and decrease expenses. In this study, a crop yield prediction system is presented that makes use of a Weighted Gradient Regression model to make its predictions. In order to accurately forecast the yield, the model that was suggested takes into account a number of different characteristics, some of which include temperature, humidity, light, moisture, and pH. The input data are segmented, and an estimate of the output is calculated based upon that gradient of the attributes of each segment individually. The Weighted model gives priority to the parameters based on their effect on crop growth during different stages of crop production.

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LIST OF ABBREVIATIONS

RDF	Resource Description Framework
IoT	Internet of Things
ICT	Information and communication technology
ML	Machine learning
UAVs	Unmanned aerial vehicles
IR	Infrared
FMIS	Farm-Management-Information Systems
W3C	World Wide Web Consortium
URLs	Uniform Resource Identifiers
RDF	Resource Description Framework
XML	Extensible Markup Language
JSON-LD	JavaScript Object Notation for Linked Data
Turtle	Terse RDF Triple Language
PAMS	Precision Agriculture Monitor System
ASCM	Agriculture supply chain management
DMVO	Multi-verse optimizer with overlapping detection phase
SLR	systematic literature review
HM&D	Health monitoring and diagnostic
APIs	Application Programming Interface
AFSC	Agricultural and Food Supply Chain
CNNs	Convolutional neural networks
LSTM	Long-Short Term Memory

TROPOMI	TROPOspheric Monitoring Instrument
MLP	Multilayer perceptron
SSTNN	Spatial-Spectral-Temporal Neural Network
MODIS	Moderate resolution imaging spectroradiometer
FAO	Food and Agriculture Organization
ANNs	Artificial neural network
MANNs	Modular artificial neural networks
GEE	Google Earth Engine
FS	Feature selection
FX	Feature extraction
ALL-F	All feature
IDE	Integrated development environment
PWM	Pulse-Width Modulation
IC	Integrated circuit
CLI	Command Line Interface
N	Nitrogen
P	Phosphorus
K	Potassium
IRI	Internationalized Resource Identifier

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Chapter1
Introduction

1.1 Overview

Precision agriculture is possible using sensors that assess environmental factors in agricultural areas [1]. Precision agriculture increases agricultural yields, production, and profitability. Precision agriculture, which collects, processes, and analyses real-time data and automates various agricultural methods, makes smart farming possible [2].

Because farming is dependent on the weather and other environmental conditions, such as temperature, humidity, rainfall, hail, as well as animal diseases, pests, and market pricing, it is difficult to forecast the outcome of a farming venture. Due to its interoperability, scalability, pervasiveness, and inclusivity, IoT is a smart farming solution. Due of its excellent scalability; the agricultural business is adopting IoT technology because of their tremendous potential [3].

Implementation of Agriculture-related IoT frameworks has a number of benefits, such as providing the farmers with informative data about the current conditions of the crop, suggesting preventive measures through which the farmers' crops, livestock, and overall production can be protected etc [4]. In addition to this, it is compatible with the complete smart system that is employed in the farms, and information can be readily transmitted across a broad range of different components. This is a significant advantage. The motivation provided by the benefits of the IoT, as well as the potentiality regarding smart farming with a wide range of efficient, reliable solutions.

1.2 Smart Agriculture

The agricultural sector will have to embrace emerging technologies in order to achieve the competitive advantage that is so desperately required if it has to continue catering to the requirements of qualitative food production. Using the internet of things in smart farming and precision farming will make it possible for the agriculture industry to boost its operating efficiency with a number of benefits, such as lowering expenses, reducing waste, and improving the quality of production [5].

"Smart farming" is the latest method for generating nutritious, environmentally friendly food [6]. It refers to the growing usage of ICT in contemporary agriculture. Internet of Things-based smart farming uses sensors to monitor agricultural fields and manage irrigation [7]. Internet-enabled smart farming is more productive than conventional farming.

Internet of Things-based precision agriculture targets large-scale farming and other agricultural production developments. Organic farming, home farming (complicated or small regions, distinct livestock and improved transparency are these tendencies. Smart farming also tackles crop growth patterns other than large-scale farming. Internet of Things-enabled smart farming might help preserve the environment [8]. Water resource management and input/treatment optimization are potential advantages.

The use of current information and communication technology (ICT) and digital technology in agricultural production is what is referred to as "smart farming" or "digital farming [9]," which allows real-time monitoring and organisation of complicated operations in the agriculture field. Today, all of the main agricultural equipment manufacturers are primarily focused on precision farming which is a subset of smart farming.

In the industry of livestock farming, sensors are attached to the animals and cameras are installed in the stalls to capture data. The captured data is then processed and converted into information that may be analysed further to perform different tasks, such as finding the illnesses and births at an earlier stage. For such a specific use of the data, standardised data interfaces play the most important role. It is the purpose of a farm management system to offer both the means to make use of the data that is already available and the infrastructure to gather the data that is required. There hasn't been much usage of drones in agricultural sectors so far, but as digitalization continues to spread, more opportunities will arise for their use. For instance, they might be used for animal localisation via the use of infrared detection (particularly for young fawns), monitoring of soil fertilisation and plant protection. On the other hand, agricultural applications for smartphones are already available, mostly used for gathering meteorological information, identifying plant illnesses, and monitoring the well-being of animals.

Smart farming, as used in the context of agriculture, is an application that combines the usage of connected devices with new technologies [10].The enhanced interconnectivity and sensor technologies made available by IoT in the agriculture industry are directly responsible for these advantages. IoT gathers data on soil, humidity, temperature, and other variables to give a precise and accurate real-time monitoring of crops. This aids in the implementation of several practical applications for achieving high food output.

1.3 Machine Learning in agriculture

Within the scientific community, new subfields have emerged, including agri-technology and precision agriculture, which are now also known as digital agriculture. Both of these subfields heavily rely on data in their approaches, and their ultimate goal is to increase agricultural production while minimising the negative effects that the industry has on the environment. The data gathered from today's cutting-edge agricultural practices is based on a variety of different sensors. Because of this, it is feasible to have a better grasp of the operation itself (machinery data) as well as the operational environment (an interplay of dynamic crop, soil, and weather variables). This ultimately leads to choices being made that are both more accurate and quicker.

Machine learning (ML) developments have opened up new doors of opportunity, making it now feasible to untangle, quantify, and comprehend data-intensive operations in agricultural operational settings. Machine learning (ML), an area of computer science, may be described in a number of ways, each of which is as the science that gives computers the ability to learn without having to strictly follow predefined instructions. Machine learning is becoming more and more applicable in a variety of scientific subjects, and it is being used in an increasing number of scientific subfields. This area includes, but is not limited to, bioinformatics, biochemistry, healthcare, meteorological, financial sciences, automation, aquaculture, food production, and climatology.

When applied in agriculture, machine learning yields accurate values, good results and facilitates easier prediction. Calculations made by humans incur the risk of being inaccurate or delayed. The output values, results, and predictions should be perfect. Utilizing ML-based technologies in application development, results in improved performance. Manually managing a large database and performing calculations is a challenging endeavour. IoT and ML both make it simple to access the agricultural data and produce results that are both accurate and timely.

1.4 IoT in agriculture

Applications of the Internet of Things have significant potential in the agricultural sector. The use of internet of things technology in agricultural settings has led to the development of a wide variety of applications that, in the long term, might be of assistance to farmers. A few examples of these applications include the development of a model for predicting yields, the creation of an automatic irrigation system, and the use of lighting and moisture sensors to manage agricultural fields. Other examples include the creation of a system to manage agricultural fields using sensors for lighting, moisture, heat, and moisture levels.

1.4.1 IoT

Through the use of Internet of Things (IoT) technology, users are able to accomplish higher degrees of automation, analysis, and integration inside a given system. The Internet of Things takes use of technologies that have been around for some time as well as others that are still in the research and development phase. The Internet of Things is able to take use of current advancements in software, falling costs for hardware, and modern attitudes on technology.

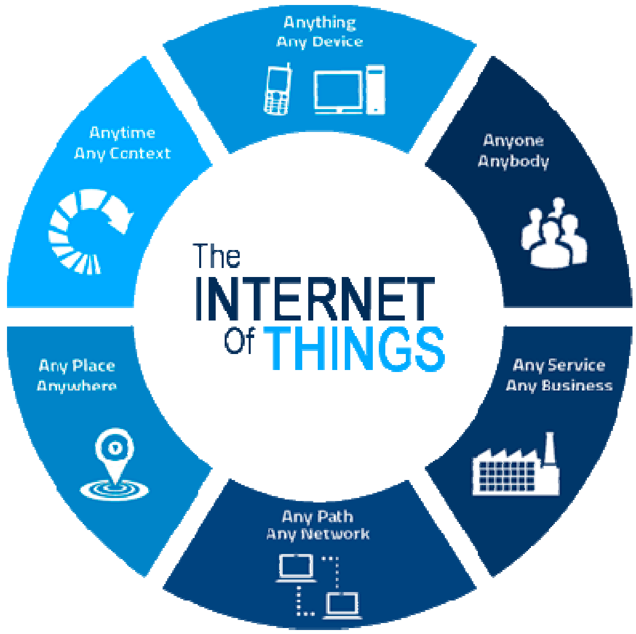

Figure 1.4.1.1: IoT Structure [11]

The Internet of Things (IoT) brings together a number of important components, the most important of which are the usage of artificial intelligence, connections, sensors, active involvement, and the use of very small devices. The use of active involvement and the utilization of tiny devices are both essential characteristics of the platform. The list that follows is a condensed version of these distinguishing qualities:

- Artificial Intelligence - Utilizing the power of data collecting, artificial intelligence algorithms, and network connections, the Internet of Things (IoT) successfully makes practically everything "smart," which means it enhances every aspect of life. This is accomplished via the use of the term "smart" technology. This may include doing anything as simple as updating the refrigerator and cabinets so that they can detect when milk and preferred cereal are getting short and then automatically place an order with the preferred grocery shop when the order is due.
- Connectivity - Because of recent advancements in enabling technologies for networking in general and internet of things networking in particular, networks are no longer only dependent on big suppliers. It is possible for networks to function on a much smaller size, at a much lower cost and yet to

do their job. The Internet of Things builds these localised networks amongst its many components.

- Sensors - The Internet of Things can't function properly without them.
- Active Engagement - A significant portion of the contact that takes place with linked technology in the modern day takes the form of passive engagement. The IoT provides the active interaction of information, products, and services.
- Devices That Are Very Small - As a result of technological developments, day-by-day devices are shrinking in size while simultaneously becoming more affordable and powerful. The IoT makes use of small devices that were built for a specific purpose in order to achieve its precision, scalability, and versatility goals.

Figure 1.4.1.2: IoT in agriculture [12]

Applications of the IoT in smart farming includes: crop monitoring, automated irrigation system, precision farming, livestock monitoring etc.

1.4.2 Sensor Technology

Agriculture sensors are the most significant part of smart farming. Various types of sensors are available, each having their own features and applicability. The data collected from the sensors can be used to better monitor and manage the crops by adjusting their practices in response to changes in the environment. It is possible to compute yields from a particular region with a high degree of precision by using a set of sensors that are installed on combined harvesters.

Table 1.4.2.1: Agriculture sensors and their functions

Agriculture Sensors	**Functional description**
Location Sensors	Using these sensors, it is possible to ascertain the latitude, longitude, as well as altitude of any location that falls within the specified zone. They are able to do this with the help of the GPS satellites.
Optical Sensors	Light is used by these sensors as a means of doing a soil analysis so that they may make more informed decisions.
Electro-Chemical Sensors	By identifying certain ions that are present in the soil, these sensors contribute to the process of compiling chemical data on the soil.
Mechanical Sensors	These sensors are utilised to measure the level of mechanical resistance as well as soil compaction.
Dielectric Soil Moisture Sensors	The dielectric constant of the soil is measured by these sensors in order to determine the degree of moisture present.
Air Flow Sensors	The permeability of air is something that these sensors measure. They can be used in either a stationary or mobile configuration.

These sensors are mounted on agriculture-related weather stations, drones, and robotics to monitor environmental conditions. Mobile applications that were expressly designed for this function may be used to exercise control over them. Because of their wireless connection, they may be managed either directly via the use of wifi or indirectly through cellular towers and cellular frequencies with the use of a mobile phone application, as indicated in the figure 1.4.2.1.

Figure 1.4.2.1: communication between sensors and mobile app [13]

The growth of plants needs water as a necessary component. Irrigation is one of those tasks that need careful planning and execution since it must strike a balance between being too much and not enough. The use of soil moisture sensors is highly helpful in measuring water levels, which provides the ability to effectively arrange irrigation events by either raising or lowering the frequency and/or intensity of such events. This ensures that beneficial nutrients will not wash away due to the heavy supply of water; on the other hand, a low water supply does not cause the plants to become dehydrated. With the use of a remote soil moisture sensor, agriculturalists are given the ability to assess the water levels in their fields even when they are not physically present there.

A soil moisture sensor is a device that monitors current soil wetness. The timing of water supply and distribution is made much more efficient with the incorporation of sensors into the irrigation system. These gauges assist in either decreasing or increasing the amount of irrigation needed for plants to achieve their full potential.

Depending on the underlying technology, soil sensors may be broken down into the following categories:

- Ground sensors are those that are buried below the ground to monitor the root zone.
- Aerial sensors are those that collect data using unmanned aerial vehicles (UAVs) and are seldom used for mapping [14-15].
- Soil moisture and satellite sensors are those that estimate the situation from space. It does not interfere with operations that are taking place on the field, which helps save money and eliminates the need for labor-intensive installations.

Crop cultivation is a dynamic process that provides sufficient justification for the use of sensors for varying terrains, phases of plant growth, climatic characteristics, and forecasting potential weather hazards etc. By performing infrared (IR) emission analysis, satellite remote sensors are able to guarantee a steady flow of data that is both trustworthy and useful. When combined with satellite images, these data provide farmers the ability to keep abreast of any changes in the levels of soil moisture and to respond in a timely way to such changes.

Figure 1.4.2.2: soil moisture sensor [16]

Maintaining an adequate water saturation level is one of the most important jobs of a farmer since it is essential for the growth of plants. A lack of irrigation causes plants to wither because they focus all of their energy on absorbing the small amount of water that is available via their roots; as a result, they have little energy left to mature and produce fruitful harvests. However, the plants are able to endure frequent stressors and continue to thrive and grow to their full potential if they are provided with an adequate amount of moisture. Excessive watering, on the other hand, leads to the rotting of the plant's roots and cuts off its supply of oxygen, which ultimately results in the death of the plant.

Soil moisture sensors for agriculture are essential equipment for farming, while online agricultural apps that include soil moisture features are effective, dependable, and reasonably inexpensive [17]. Satellite remote sensors are an outstanding example of a great deal when considering the amount of input or effort that is required to implement them in comparison to the volume of information and the quality of data they are capable of supplying. This is because satellite remote sensors are capable of supplying both. The incorporation of these practices into day-to-day farming helps to promote plant development by enabling farmers to more effectively control the hazards associated with water surplus and water deficit.

1.4.3 Farm-Management-Information Systems (FMIS)

Maintaining data and making intelligent use of it may both be assisted by FMIS. Documentation, the planning of work phases, and the management of contracts and invoicing are some of the uses for these, but they may also be used to accomplish things like transmitting orders to machines via ISOBUS. The variety of FMIS is quite wide due to the fact that there are so many kinds of various businesses. They might be as simple as a field record file or as complex as sophisticated agricultural systems.

1.4.4 Agricultural Applications

Farmers who work with smartphones frequently turn to agricultural applications. For instance, an app may be utilised to identify significant diseases that affect agricultural crops or to acquire information regarding the weather, apps providing remote access to monitor the crop conditions and growth [18-19]. Apps designed to assist with farm management provide information on cultivated areas and the areas themselves, as well as stock levels and other relevant data [20]. This data can also be used in certain circumstances to generate application data for financial assistance in agriculture.

1.5 IoT interoperability

Interoperability in the Internet of Things refers to the ability of many components within an Internet of Things deployment to efficiently interact with one another, exchange data, and work together to accomplish a common goal. The ability to transfer and comprehend data via all of an organization's connections, from devices to the cloud, is essential for every organization.

The term "interoperability" refers to the capability of two or more distinct technological systems, components of the system, or software applications to establish communication with one another, exchange data with one another, and correctly comprehend and use the information received for the purpose it was intended. Interoperability can also refer to the ability of two or more distinct software applications to communicate with one another. Interoperability refers not only to the interactions that take place within a system that is concerned with internal communication but also to the interactions that take place between two or more systems.

Finding interoperability in the IoT calls for taking a methodical approach to the job if one is to have any chance of understanding it. The internet of things is heterogeneous, and as a result, the challenges connected with interoperability may be seen from a variety of different points of view. There is nothing innovative about the concept of heterogeneity, nor is it exclusive to any one area of study. However, even though their languages are different, individuals are still able to interact with each other through the use of a translator (whether it be a human or a tool) or a shared language. In a similar spirit, the numerous components that make up the Internet of Things (devices, communication, services, applications, and so on) should be able to interact with one another and communicate with one another in a seamless way so that the ecosystem may attain its full potential.

Interoperability requirements for IoT installations fall into three categories:

- Compatibility in terms of technology: The deployment is equipped with the capability to transfer data bits by using a physical communications infrastructure.
- Interoperability in terms of syntax: The data may be structured using a shared syntax or a common information model, which also creates a mechanism for sharing the information as specified typed data.
- Deployments of a semantic Internet of Things need to have the capacity to determine the meaning of the data.

1.5.1 Interoperability challenges

The existing difficulty of connected devices is to communicate successfully when deployed, which has hampered the adoption of linked devices and resulted in increased costs and decreased value for many applications of the IoT. Interoperability in IoT deployments may be difficult to address and expensive to pay for, which might cause IoT projects to fail or move at a much slower pace.

Not only does the absence of automated and broad interoperability slow down the consumer and residential IoT sectors, but it also slows down the progress made in the deployment of IoT in municipal and commercial settings.

1.6 Semantic Web

The Semantic Web is a network of interconnected data sets that are organised such that computers can read the data more easily than humans can. Because of this, analysing data using the Semantic Web is more effective than using conventional techniques. It combines a useful method of data presentation in the form of a globally connected database, and it is plausible to think of it as an expanded version of the Wide Web that currently exists. You may consider it an enhanced version of the current World Wide Web. The Semantic Web will transform the current Internet, which is composed of texts that are not organised in any specific manner, into a knowledge and data-based network. A crucial step toward reaching this goal is the ease with which the Semantic Web makes it possible to incorporate semantic content into WebPages.

The World Wide Web Consortium (W3C) is the driving force behind the Semantic Web. It is often constructed using syntaxes that make use of Uniform Resource Identifiers (URIs) to describe data, and it is based on the Resource Description Framework (RDF) that was developed by the W3C. The collective name for these syntaxes is "RDF syntaxes." The incorporation of data into RDF files makes it possible for computer programs or web spiders to search for, uncover, gather, evaluate, and analyze data found on the World Wide Web.

The primary objective of the Semantic Web is to catalyze the development of the traditional Web so that users may search for information, find new information, exchange information, and integrate information together with less effort. The World Wide Web enables humans to accomplish a wide variety of jobs, such as the booking of online tickets, the investigation of a variety of information, the utilization of online dictionaries, etc. However, robots are not yet capable of carrying out any of these duties without the assistance of a human being. This is due to the fact that web pages are designed to be read by people, not machines. It is possible to think of the Semantic

Web as a vision for the future in which data may be easily translated by computers, so enabling them to carry out a variety of laborious activities linked to finding, combining, and acting upon the information that is accessible on the Web.

Semantic Web makes it possible for robots to swiftly comprehend and respond to complex human queries while taking their meaning into consideration. To achieve this level of comprehension, the right knowledge sources have to be semantically organized, which is a challenging endeavor.

The first contribution of the semantic web to IoT is in the transformation of data collected by objects. Semantized data can take the status of useful information. Once put back in a global context and interpreted, this information can be transformed into knowledge. From data to information, the transformation consists of annotations and linking with ontologies. This enrichment can be done at different stages of the data's life cycle: at creation, before or after storage.

Because of the inclusion of metadata, the data are no longer limited to the programme that had them in the first place. The integration of the data into the network of connected information is a key component of the role that the semantic web plays in the Internet of Things. The information that is created by the object network may then be analysed once it has been semanticized.

1.7 Resource Description Format

A general framework that can be used on the web to describe data that is connected to other data is the Resource Description Foundation, often known as RDF. A set of triples called an RDF statement is used to define and transmit metadata. As a result, it is possible to exchange data in a standardised manner based on the relationships between the data parts.

RDF is used in the process of integrating data from a variety of sources. When information is organised according to meanings, this is known as the semantic web, and it is built on top of the RDF framework.

A directed graph that maps the connections between entities is made up of collections of RDF assertions that are connected to one another. An RDF graph that illustrates the connections between various things may be built with the help of a set of RDF statements that describe the items in question.

The World Wide Web Consortium (W3C) is in charge of the maintenance of the RDF standards, which include the underlying principles, semantics, and specifications for a variety of formats. The Extensible Markup Language (XML) served as the foundation for the original syntax that was developed for RDF. Other syntaxes, such as JavaScript Object Notation for Linked Data (JSON-LD), N-Triples, and Terse RDF Triple Language (Turtle), are currently being used more often than ever before.

Benefits of RDF

The availability of an open as well as interoperable standard for the interchange of data and metadata is necessary for the semantic web. This is exactly what RDF offers, which is why it was first standardised in the first place. The following is a list of the advantages of using RDF:

- The exchange of metadata about online resources is made easier with a framework that is standardised.
- The RDF standard syntaxes for describing and querying data make it possible for software that utilises metadata to function in a more straightforward manner.
- The standardised query capabilities and syntax make it possible for apps to more easily share information with one another.
- Users searching based on metadata get more accurate results than they would if they searched using indexes that were generated by collecting full-text information.
- Intelligent software agents are able to deal with more exact data, and as a result, the information that they offer to consumers is also more precise.

1.8 Agriculture ontology

Ontologies are also seeing increased use in the agricultural sector, where they are being put to a variety of purposes, the facilitation of agricultural knowledge sharing among farmers located all over the world and in a variety of languages, and the provision of support for farmer decisions by way of the provision of automatic knowledge inference. In addition, agriculture contains a huge number of concepts, the majority of which are referred to by a variety of names but have the same meaning and are segmented into a number of distinct organisational structures.

The capacity to integrate and harmonise vast quantities of agricultural information, originating from a wide variety of sources and in a variety of forms, has recently been recognised as a fundamental prerequisite for sustainable agriculture. The existence of each of these facets of agricultural knowledge demonstrates the need of incorporating ontologies into agricultural practise. Agriculture Ontologies provide farming applications not just the ability to reason but also to perform many functions with more consistent and reliable data. The models developed with the use of Agriculture Ontology are able to adapt to the expansion of the amount of data without having an effect on the processes and systems that are depending on it, even if anything goes wrong or has to be adjusted.

1.9 Motivation

Farmers may see long-term advantages from the usage of IoT devices in agriculture, including higher production, lower overall costs, and less wasteful use of resources like water and power. The enhanced interconnectivity and sensor technologies made available by IoT in the agriculture industry are directly responsible for these advantages. One of the major hurdles is still making the Internet of Things accessible and interoperable. Semantic interoperability provided by the Semantic Web enables meaningful communication across various IoT devices and technological platforms. In order to carry out tasks more quickly and accurately, such as multidimensional analyses of crops, automated irrigation, remote monitoring of crops, plant disease prediction, weed identification, yield prediction, etc., the heterogeneous data generated from various IoT devices needs to be consistent, reliable, and meaningful.

1.10 Problem Statement

Semantic Interoperability in the Internet of Things refers to the efficient deployment of Internet of Things frameworks with the ability to interact with one another, exchange data in a meaningful way, and work together to accomplish a common goal. To provide the semantic interoperability in Agriculture IoT systems, there is a need of a common knowledge base which provides definitions of concepts, terms, instances, and IoT devices metadata related to the Agriculture domain. Semantically annotated data provides a common vocabulary, which enables IoT devices and agriculture applications to share information in a meaningful, useful manner. The primary objective of this study is to develop an efficient semantic knowledge base with the goal of achieving semantic interoperability in IoT devices that are utilized in smart agriculture applications. This knowledge base will have the capabilities of crop selection, effective sensor data collection, analysis, and yield prediction, all of which will assist farmers in achieving higher yields.

1.11 Objectives

- To review the current issues and challenges faced in interoperability of heterogeneous IoT devices.
- To propose a framework for providing semantic interoperability in IoT used in smart agriculture.
- To develop a semantic knowledge base (Ontology) for agriculture IoT devices to make interoperability effective.
- To develop an accurate yield prediction model using machine learning and create a user interface (Website) that facilitates the user with access to the developed frameworks, crop selection, crop monitoring, and yield prediction.
- To validate the performance of the yield prediction model.

1.12 Thesis Outline

Chapter 1 presents the introduction to the thesis. The concepts of Smart Agriculture, Machine Learning, IoT in agriculture, and Semantic Web have been discussed in detail. An introduction to Resource Description Format and agriculture ontology has been presented. The Motivation, Problem Statement, and Objectives of the research have been elaborated.

Chapter 2 discusses the literature review carried out to identify the problems in implementing IoT and the semantic web in Agriculture. Recent articles published in the fields of IoT in agriculture, IoT Interoperability in agriculture, agriculture ontology and crop yield predictions have been discussed in detail.

Chapter 3 presents the tools used for IoT System Setup in Agriculture Field. Arduino board and the components have been discussed. The interfacing of Temperature and humidity sensor, soil moisture sensor and pH sensor with Arduino has been discussed in detail. A brief description of the ThingSpeak Cloud Framework is also presented.

Chapter 4 presents the proposed methodology in detail. The proposed framework, including crop selection, agriculture ontology Development, IoT based crop monitoring, RDF working and crop yield prediction, is presented.

Chapter 5 presents the implementation and results of crop selection, ontology for IoT in Agriculture, Data parsing and Ontology updation and Yield Prediction.

Chapter 6 presents the results discussion and validation. The performance metrics R^2, MSE, and RMSE for evaluating the developed prediction model are explained in detail, and the comparison of the performance with other models is presented.

Chapter 7 presents the conclusion and future scope. The contribution of the developed ontology for providing the semantic interoperability in IoT used in Agriculture is explained, and the future scope of further research in IoT, semantic Web technologies for providing more advanced Agricultural applications is presented.

Chapter2

Literature Review

2.1 Introduction

Agriculture is a necessary sector that needs to maintain a healthy equilibrium with the expansion of the population. Nowadays' work in the Agricultural fields has become very smart by using most of the developed technologies such as Big Data, IoT, Block Chain etc. This helps in improving the quality of production, saving working time, reducing labor for the work, providing yield prediction facilities to get better yield, and also to maintain the financial details to get the profits etc.

Olmstead et al. [21] analyzed and explored of some of the conceptual difficulties connected with the usage of induced innovation and threshold models. These models are paradigms that are often used to explain the dissemination of technologies and agricultural systems. A greater knowledge of these models, as well as the more general experience of people all over the world, hints that it may be essential to reevaluate several crucial questions about the growth of agriculture in Europe.

Wang et al. [22] used the sensors to monitor humidity, temperature and moisture. Then the sensed information is conveyed to the farmers by alerting them via third parties such as meteorological stations. The detected information makes the farmers easily integrate the information and get a clear option for the delivery of particular things, which resulted in an increase in both their pay and the statutory criteria. In addition, the author McCown R.L. [23] provides a similar concept together with the other authors. Using the farmer's interior layout to collect data enables the creation of information that may be used to learn and construct an authentic intellectual framework.

Allen and Wolfert [24] presented a number of different patentable methods that might provide farmers with assistance in monitoring their farms in a more effective manner. Nikkila R et al. [25] found more sophisticated frameworks that monitor geographical regions and climatic conditions.

Ayday and Safak [26] defined two main areas of use for precision agriculture based on IoT. These areas of application were leveraged to acquire and analyze information in order to monitor the supply chain goods depending on changes in the environmental conditions. IoT will automatically change the data that has been gathered into a sequence of operations that will be carried out by the actuators. In addition to this, it assists in the optimization of processes, the management of complex autonomous systems, and the consumption of resources.

Sensor technology is used in the agriculture industry to solve issues with yield and the suggested technique of monitoring. The network layers' usage of sensor technologies was described by Sahota et al. [27]. The crucial role that sensor technology performs in agriculture and the essential elements that go into it were described by Mampentzidou et al. [28]. A sensor that was suggested by Shining Li et al. is used by the Precision Agriculture Monitor System (PAMS) in order to monitor agricultural activities. The IFarm Framework system is proposed as a method for controlling the amount of water used in order to boost productivity by increasing the importance of socioeconomic variables. Anisi M.H. et al. [29] categorized the sensor technology according to the performance parameters it exhibited.

Himanshu Sharma et al. [30] proposed employing ambient solar energy harvesting to recharge WSN node batteries to overcome the constrained energy availability design problem. Solar energy harvesting faces electricity intermittency, solar energy prediction, heat problems, solar panel power efficiency, as well as environmental difficulties. Solar energy gathering prolongs WSN networks in this investigation.

Hemathilake et al. [31] explained the technologies and how they may be used to advance agricultural yield to boost the amount of food that is produced in order to satisfy the growing demand from the world's population.

Achilles D. Boursianis et al. [32] reviewed current agricultural IoT and UAV research. The writers examine the core concepts of IoT technology and smart farming applications and solutions. They also analyse UAV applications in smart agriculture to determine their function.

Sana Rafi et al. [33] analysed current research, especially that from the previous five years in related sectors, to find the most effective as well as harmonious AI practices to help producers increase productivity and quality.

Maria Kernecker et al. [34] suggested that taking farmers into account while also paying attention to elements at the farm and system level might assist in identifying obstacles and opportunities for the implementation of EI. In order to do this, the authors turn at many bodies of literature that intersect with one another and cover a variety of topics, including EI practice specifics, systems thinking, and farmer acceptance. One of the frameworks that has been used in the research on farmers' acceptance of new farm management tools and practices is the innovation characteristics framework.

2.2 IoT in agriculture

Jirapond Muangprathubet al. [35] recommended using a wireless sensor network to irrigate agricultural crops. They designed and developed an agricultural field control system combining node sensors and a smartphone app as well as online application to handle data. Hardware, online application, as well as mobile application comprise the system. Control box hardware for agricultural data collection was the first component. Control box-connected moisture sensors monitor the field. Data mining was used to forecast crop growth temperature, humidity, as well as soil moisture levels. The final component controls crop watering via mobile app. In the functional control mode, the user has the option of manually controlling the amount of water that is applied to the crops. The LINE application can receive notifications from the system with the help of LINE's application programming interface.

Muhammad Shoaib Farooq et al. [36] covered several agricultural IoT technologies. IoT-based smart farming's main components are listed below. IoT-based farm network technologies have been extensively explored. Internet of Things-based agricultural systems may be linked to cloud computing, large data storage, and analytics. Along with worries about the Internet of Things' impact on agricultural security, a list of smartphone and sensor-based farm management applications was released. We also examined certain nations' IoT-based agricultural legislation and successes.

He Jiang et al. [37] presented a technique that may quickly stop infections induced by environmental causes and identify illnesses in apple fruit. Deep learning, a method that has proven effective in image processing and classification, is used to categorise Apple photographs. A deep neural network with a range of convolutional layers and a diverse neuronal population is subjected to analyses and evaluations.

Kamlesh Lakhwaniet al. [38] presented a process of storing the data from the sensors in blockchain and developed a smart contract that has been deployed on the Ethereum blockchain, which will make easy buying and selling of crops lands.

Sunil Luthra et al. [39] presented IoT-based agricultural supply chain. Six IoT technologies are used in agriculture supply chain management (ASCM). IoT might boost India's agricultural supply chain by reducing food waste and better addressing end users' demands in a sustainable and effective way. IoT-based technology offers great promise for ASCM integration in an industrial context in India.

Mohamed Abdel-Basset et al. [40] proposed the multi-verse optimizer with overlapping detection phase (DMVO), an enhanced metaheuristic method. DMVO maximises WSN area coverage.

Muhammad Shoaib Farooq et al. [41] surveyed Internet of Things techniques as well as their current use in agricultural application fields to produce a systematic literature review (SLR). The underlying SLR was calculated using peer-reviewed research publications from 2006 to 2019. 67 carefully selected articles were categorised. Their thorough analysis collects all important studies on Internet of Things agricultural applications, sensor systems, communication protocols, as well as network kinds. A platform for the IoT in farming contextualises a broad range of agricultural solutions. IoT-based agricultural policies are also given.

Wan-Soo Kim et al. [42] categorised and examined using previously obtained data, agricultural IoT applications. Agriculture uses sensor and communication technology.

Based on the investigation, IoT's benefits and drawbacks in agriculture were discussed.

GodloveSuila Kuaban et al. [43] examined emerging country IoT agricultural implementation challenges. The authors think this design should be IoT-independent. This framework starts with IoT devices and agricultural systems.

E. Suganya et al. [44] developed built a plant disease detection model utilising image analysis and IoT. Smart farming uses the latest Internet of Things (IoT) technologies to create nutritious, ecologically friendly food. The plan uses modern information and communication technologies to reduce waste and maximise agricultural productivity. Agriculture binds the world together. The planned Internet of Things technology enables more precise disease diagnosis in plants, with a particular emphasis on the region that is afflicted. Additionally, it describes the likelihood of drawing inaccurate conclusions, which in turn lessens the likelihood of taking inappropriate measures to ensure the health of the plants grown. The suggested method will also have the capability of predicting the extent of damage caused by pests to plants, which will allow for suitable measures to be taken to optimise plant output. Techniques such as pattern recognition and digital image processing will be used in order to process and analyse the digital photos that were collected from the plants. These pictures will be segmented using the proposed image analysis methods to identify the illnesses and the afflicted level.

Raquel Gómez-Chabla et al. [45] presented a detailed overview of Internet of Things-based agricultural tools as well as applications research (IoT). Discussing IoT-based application software for agriculture, IoT devices used in agriculture, and the advantages of these technologies has offered a full review of IoT applications in agricultural.

Neeraj Gupta et al. [46] explored the best health monitoring and diagnostic (HM&D) technology to boost field productivity and lower equipment costs. The correlation between data may be visualised to make conclusions that will allow the future HM&D technological change.

Miguel A. Guillén et al. [47] Investigated rural edge computing to address AI-IoT gaps. The experiments show that cloud-based techniques are still underperforming.

Meghna Raj et al. [48] offered a detailed overview of how the IoT, big data analytics, deep learning, and machine learning may be utilised to control agricultural operations. Agriculture 4.0 uses each of these technologies in detail. Their analysis also highlights important research gaps that must be solved before Agriculture 4.0 could fully exploit these technologies.

Yu Tang et al. [49] provided an in-depth analysis of 5G's current and potential future applications in agriculture.

Nebojša Gavrilović et al. [50] presented an overview of the various software architectures now available for usage in IoT systems throughout the smart city, healthcare, and agricultural domains. The research included recommendations for fixing the issues, including enhancing different kinds of software architecture and the relationships between the parts of that design that were singled out. Software architectures for the IoT have been examined at length, including layered architecture, service-oriented architecture, and cloud-based architecture.

Godwin Idoje et al. [51] provided an in-depth examination of the smart technologies now in use in farming and explains the state-of-the-art tools presently at farmers' disposal; these tools include IoT, cloud services, machine learning, as well as AI. It is explained how "smart farming" can be used not only for the production of crops and animals but also for tracking their period after harvesting. The authors' research contributed to the body of knowledge by reiterating the difficulties that intelligent technology poses to agriculture and the problems that have been recognised within the context of current frameworks for smart agriculture were outlined.

Konstantina Spanaki et al. [52] offered as a paradigm for the management of data in artificial intelligence applications that include several parties. The authors' proposed method makes use of design science principles to construct AI-powered role-based access control. In order to successfully limit access, data management and dissemination must comply to defined contextual laws.

Nermeen Gamal Rezk et al. [53] propose an IoT-based smart farming system and a machine learning-based approach for predicting crop yield and drought to serve as reliable decision-making aids for farmers. This method is called WPART. Farmers and agribusiness executives place a high value on drought and crop yield predictions. To better understand the physical process of drought and to increase forecasting abilities, researchers have been looking into the topic of drought prediction. With the use of a wrapper feature selection technique and PART classification methodology, this research has established a smart strategy for agricultural productivity and drought predictions. Their suggested method estimates result from five distinct datasets.

Abhishek Khanna et al. [54] studied the developments of IoT in precision agriculture and the roles played by a variety of researchers and academicians during the last several years. Potential future study avenues and the difficulties presently experienced in agricultural operations have also been highlighted.

2.3 IoT Interoperability in agriculture

Juan Antonio López-Morales et al. [55], developed a data model to better manage agricultural land in irrigation villages while keeping tabs on crop needs. The core of the platform is made up of standardised open interfaces as well as protocols, and they are used to centralise all of the data into a single data model.

Kushankur Dey et al. [56] demonstrated data collection using Internet of Things gadgets with blockchain technology for data validation.

Ioana Marcu et al. [57] offered the Arrowhead Framework in IoT/SoS smart city and smart farm designs. Their poll seeks to explain the Arrowhead Framework's global performance impact.

P. Salma Khatoon et al. [58] focused on interoperability for internet-connected agricultural equipment. The framework allows device compatibility. Farm sensor data is semantically tagged and user-friendly. A lightweight semantic annotation model annotates data. RDF gives data semantics.

Sahin Aydin et al. [59] proposed semantic and syntactic data integration. Creating and testing an open-data platform proves the method's potential. Their work also shows how to use web services and APIs to syntactically interoperate sensor data in agriculture (APIs).

The article by Maximilian Treiber and colleagues [60] explored the ways in which interface functions and middleware may enhance the data flow commodities that are utilized by farmers.

Gunasekaran Manogaran et al. [61] optimized agricultural information scheduling and classification, reducing process delay and stagnancy. Smart farm control flexibility is measured by yield delay and stagnancy. The classification step categorises information by processing time to reduce backlogs and speed up unloading.

Vippon Preet Kouret al. [62] discussed agricultural Internet of Things hardware and software. The writers also discuss global public and private sector efforts and startup enterprises offering intelligent and environmentally friendly precision agricultural solutions. Precision agriculture's current state, research potential, restrictions, and prospects are briefly discussed.

Olakunle Elijah et al. [63] demonstrated the internet of things ecosystem and how DA makes smart agriculture feasible. The writers also predict technology advances, application possibilities, business, and marketability.

Vaibhav S.Narwaneet al. [64] conducted an analysis of the key elements that play a major role in the adoption choice of IoT in the Agricultural and Food Supply Chain (AFSC). The authors determined that there are 24 crucial criteria by conducting an extensive literature review and soliciting the feedback of industry professionals. The list of elements that were discovered was then broken down into categories such as technical, social, economic, and organisational. In order to establish the nature of the link between these elements and their effects, the DEMATEL approach was used.

Symphorien Karl YokiDonzia, et al. [65] proposed a structure for the implementation of IoT Gateway in precision agriculture. IoT architecture, platforms, standards, and compatible technologies beyond adopters have been considered. Establishing as many connections as possible between various sensors and connected devices, as well as developing intelligent breeding systems, is the primary objective of their study.

WenTao et al. [66], summarised recent research on smart farming and Internet of Things connectivity technologies.

Beniamino Di Martino and colleagues [67] offered a framework for the development of an expert system that makes use of ontologies to enable intelligent management of irrigation systems. Padmalaya Nayak et al. [68] discussed modern agricultural apps that provide farmers decision-making tools and lower manual labour costs. The IoT seamlessly integrates goods, information, and services, increasing corporate efficiency, quality of products, as well as profit. Current IoT in agriculture studies examine large-scale agricultural food industry difficulties, restrictions, advantages, and hazards.

Manlio Bacco et al. [69] provided a survey of recent research initiatives and scientific literature to show outcomes, ongoing research, and unsolved problems. The primary area of concentration is on the territory of the EU; after identifying potential dangers and worries, the authors investigate current and potential solutions to overcome the obstacles they face.

Tamoghna Ojha et al. [70], examined IoT architecture, communication, as well as middleware technologies and their particular challenges. After that, the authors discuss several agricultural IoT applications. To analyse the solutions' design and execution, they exhibited many case studies. Thus, they assessed the different modelling tools, data sets, and testbeds available to explore with IoT in agriculture. They highlighted the IoT in agricultural problems and issues.

SergioTrilleset al. [71] demonstrated an inexpensive Internet of Things-based sensorized platform for weather monitoring. The software will apply an alert disease model to vine farming. In order to accomplish this goal, the edge computing paradigm is being utilized. Furthermore, the work follows some recent developments in GIScience in order to improve interoperability.

Ajeet S. Poonia et al. [72] examined a range of concerns and obstacles that arise when IoT devices are employed in smart agriculture and highlighted the usability and usefulness of wireless networks and other relevant terms. Explores smart agriculture, IoT, and wireless network improvements. The authors also suggested research paths to enhance the system's economics, operations, and technological viability.

Muhammad Shoaib Farooq et al. [73] classified and summarised the cattle sector IoT research. Thus, cattle management IoT network design, topologies, and platforms have been extensively discussed.

Cor Verdouw et al. [74] developed an architectural framework for describing Internet of Things-based agricultural and food systems.

Sahin Aydin et al. [75] suggested that micro services may solve long-standing WSN-based system challenges including heterogeneity, interoperability, scalability, mobility, stability, and maintainability, according to the authors. A sustainable WSN-based beehive observation system was created.

Bam Bahadur Sinha et al. [76] provided an in-depth discussion of the agricultural industry's most important components, recent innovations, most pressing security concerns, difficult obstacles, and most promising future trends. The authors provide a comprehensive update on current developments and focus on them in detail. Their survey's objective is to assist upcoming researchers in identifying pertinent Internet of Things issues and selecting appropriate technological solutions depending on the needs of the application.

Vendor lock-in, the inability to design an Internet of Things application that exposes cross-platform and/or cross-domain functionality, and the difficulty of connecting non-interoperable Internet of Things devices into multiple platforms cause these interoperability issues [77]. These issues limit Internet of Things adoption. Multiple IoT systems from various suppliers may seamlessly cooperate and share resources. Several academic, business, and standards groups have worked to improve IoT interoperability and resource sharing amongst devices from various suppliers.

Interoperable protocols, architectures, standards, as well as technologies have been enhanced and adapted for industrial applications in recent years. There are no current survey studies on IIoT interoperability. The authors [78] examined both old and contemporary IIoT technologies, frameworks, as well as solutions to improve interoperability.

The expansion of IoT has highlighted the need for interoperability throughout the industrial sector [79]. Software, equipment, as well as control systems utilised on the shop floor to internet-accessible cloud-based platforms that provide a range of services on demand are covered. Thus, smart manufacturing interoperability would improve communication and data sharing across machines, sensors, controllers, users, systems, but also platforms. Data exchange is error-prone. Machine and software architecture and platforms hinder this purpose.

In [80], the authors have surveyed the most prevalent architectural options that are available today to design an Internet of Things system. These solutions range from architecture that has already been standardized to commercial architecture. A consistent reference for security and interoperability evaluation has been established by comparing, analyzing, and mapping the elements that make up such systems against one another. Existing Internet of Things security as well as API interoperability solutions have been analysed.

2.4 Agriculture Ontology

Quoc Hung Ngo et al. [81] Created a knowledge base for an ontology of agriculture that can be applied to the development of intelligent agricultural systems. This ontology contains fundamental concepts from the agricultural domain, in addition to sub-domains pertaining to geography, the IoT, business, and other knowledge gleaned from a variety of datasets. Any user can easily understand agricultural data links between each other when using this ontology, and these links can be collected from a wide variety of data resources.

P. Sanjeeviet al. [82] presented Ontology-enabled IoT extracts attributes. Counting critically post-harvested Sekai-ichi apples is easy. The hierarchical Post-Harvest model prevents post-harvest losses and deficiencies and quickly identifies trash to keep agriculture healthy and separate from its surroundings. The lower, middle, and higher processing techniques were used for separation. By focusing on identifying a negative shift, the intermediate level is being generalised.

Yi Wang et al. [83] generated and integrated citrus production data. The Eight-Point Charter of Agriculture divides citrus knowledge into eight areas and develops links within each category. The citrus production knowledge framework has eight categories and links.

D Thenmozhiet al. [84] recommended a Tamil–English CLIR method. This method obtains pages in English by translating Tamil queries. To resolve Tamil question ambiguity, a word meaning disambiguation module was deployed. An automated English ontology is used to address English inquiry ambiguity. To translate Tamil queries into English, the authors created a morphological analyzer, multilingual dictionary, and named entity database.

Brett Drury et al. [85] offered a self-contained reference strategy to stimulate semantic web study on agricultural concerns.

Sahin Aydin et al. [86] suggested proposing a general ontology-based data acquisition paradigm to construct MVC-based data collection forms for agricultural open data platforms. OWL2MVC, which uses the Hazelnut Ontology, was created to show how well the suggested model generates data collection forms. Because model construction follows ontology class selection, OWL2MVC Tool users may easily and independently create data gathering forms.

Murali Elumalai et al. [87] provided an ontology-based knowledge base for the purpose of storing information regarding the various components that make up soil composition. The ontology supplies a structured and formalised body of knowledge, which is then mined for various patterns. As a result, recommendations are made regarding the types of crops and the soil compositions that are best suited for growing crops.

Julie Ingram et al. [88] presented a search engine's user-centered ontology construction strategy. The search engine helps farmers and advisors identify relevant research. Subject matter experts, advising practitioners, as well as stakeholder groups participated in 10 European case studies.

Neha Kaushik et al. [89] outlined a plan for the creation of an ontology that is specific to the agriculture domain. The strategy that has been suggested will work in two stages. Domain-dependent regular expressions as well as natural language processing extract agriculture-related words in the first step. The writers will next identify semantic links between extracted words and sentences. RelExOnt, a rule-based reasoning algorithm, is suggested for the task.

Shyama I. Wilson et al. [90] explored system as well as software engineering quality ideas to adapt and improve ontology engineering principles. The authors developed an ontology quality strategy to help developers construct high-quality ontologies and viable ontology-driven DSSs. The approach was shown using an agricultural use case.

Nidhi Malik et al. [91] presented two objectives. The first purpose is to create a natural language interface for the ontology based on agricultural fertilisers, and the second is to design and develop it. An ontology takes long to create since it requires professional and physical labour. One of the key aims of ontology design and development in agriculture is to make it usable in real-world circumstances. The generated ontology's real-time applicability will be enhanced by integrating it with crop or soil ontologies. An interface that employs normal language to connect with the ontology, provides information to the user.

Clément Jonquet et al. [92] presented the content and features of the platform, including the additions that were made to the technology that was initially developed. Five primary agronomic use cases helped create and embed the initiative in the community. AgroPortal is a powerful and feature-rich resource for the agronomic domain that builds on biomedical knowledge and technology.

Javier Lacasta et al. [93] presented a suggestion system to simplify pest identification and treatment. Their suggested system relies on a crop-pest-treatment ontology.

R. Shyama I. Wilson et al. [94] created an iterative quality technique by analysing ontology engineering and software engineering quality theories and applying them to quality concerns. The authors show their technique and explain how different ontology quality theories relate to it. A use case in agriculture shows how the technique may be utilised in real life. To refine and prove the technique, further trials are expected in the future.

R. M. D. C. Rathnayaka et al. [95] discussed the ways in which the structure of a created ontology may be maintained by collaborative efforts. By storing the ontology on a central server, this work employs a synchronous collaborative research methodology. Through intuitive web-based interfaces, collaborative partners have the ability to make changes to the ontology and ensure its continued upkeep. Every user is aware of the changes that are made to the ontology in real-time as they occur since the ontology is stored in a single location. The sorts of modifications drive the generation of different versions of the ontology. If the change would have an effect on the previous versions' compatibility, a new version will be developed; otherwise, the existing version will be updated. The semantic versioning standard is used so that various versions may be distinguished from one another. The implemented system undergoes independent validation as well as evaluation with the assistance of a user group.

Nikolay Teslya et al. [96] focused on presenting the environment and the states of the robots in a smart space while they are working together to solve a task. Gazebo and ROS model and see the interaction process. The authors described robots' equipment and physical traits in their ontology. Fuzzy sets assess some ideas to allow robots to interact differently.

An ontology-based insect pest management decision support system was presented by Katty Lagos-Ortiz and her colleagues [97]. The system was designed for use with sugarcane, rice, soya, and cocoa crops. This system makes use of Semantic Web technologies to record the knowledge of experts and applies semantic reasoning in order to identify insects that cause damage to crops.

Bruno Guilherme Martini et al. [98] proposed a computer model IndoorPlant for indoor agriculture. The analysis of context histories is utilised by the model in order to provide intelligent generic services. These services include the prediction of productivity, the indication of potential issues that may arise with cultivation, and the provision of suggestions for improvements to be made to greenhouse parameters.

With hydroponic production data gathered over the course of seven months from the cultivation of radicchio, lettuce, and arugula, IndoorPlant was put through its paces in three different situations that mimicked the day-to-day activities of farmers.

Leonid Gokhberg et al. [99] proposed an innovative method for identifying emerging technologies in specific industries and researching how they will evolve in the future. Based on text-mining research, the first stage presents the ontology of developing technologies in global agriculture and food. Text-mining methods pooled these technologies in the second stage. These were: (1) technical market projections and (2) their potential to solve sectoral and national problems. This research, supplemented with big data, identified opportunities for Russian aerospace and defence science and technology development.

Gilson Augusto Helfer et al. [100] developed an architectural model utilising Partial Least Squares Regression to assess soil fertility and productivity based on history.

2.5 Crop yield prediction

Thomas van Klompenburg et al. [101] searched six different electronic databases and obtained 567 relevant papers. Then they narrowed the field down to 50 articles that met both the inclusion and the exclusion criteria in order to conduct a more in-depth analysis. They conducted a thorough investigation of the chosen studies, examined the procedures and characteristics that were used, and offered recommendations for more studies.

Anna Chlingaryan et al. [102] presented new advances in machine learning-based agricultural production estimation as well as nitrogen status estimate. 15 years ago, these advancements happened.

DhivyaElavarasan and colleagues [103] came up with the idea for a deep reinforcement learning technique, which combines reinforcement learning with deep learning in order to construct a framework for agricultural production prediction.

Convolutional neural networks (CNNs), a deep learning technique that excels in image classification, are used to develop a crop yield prediction model using UAV

NDVI and RGB data, as detailed by Petteri Nevavuori et al. [104]. CNNs are a deep learning approach that excels in image classification. This model employs UAV data.

P.S. Maya Gopal et al. [105] explored MLR-ANN fundamentals. An MLR-ANN hybrid model can reliably estimate agricultural yields.

Raí A. Schwalbert et al. [106] proposed a novel model using Long-Short Term Memory (LSTM), Neural Networks, satellite imaging, and meteorological data to predict southern Brazil's soybean output in-season.

Bin Peng et al. [107] examined three satellite-based SIF solutions for their ability to forecast Midwest maize and soybean yields. The TROPOspheric Monitoring Instrument (TROPOMI), Orbiting Carbon Observatory 2, and Global Ozone Monitoring Experiment-2 provided gap-filled, novel, and coarse-resolution SIF retrievals. SIF-based yield prediction models were compared to satellite-based vegetation indices (VIs).

Shital H. Bhojani et al. [108] suggested a multilayer perceptron (MLP) neural network with a new activation function, updated random weights, as well as revised bias values for meteorological parameter datasets. The authors evaluate numerous activation functions and propose some new basic ones to improve neural network performance and accuracy. DharaSig, DharaSigm, and SHBSig are the novel activation functions. DharaSig1, DharaSig2, and DharaSig3 were also created by significantly modifying the DharaSig function.

MengjiaQiao et al. [109] proposed the Spatial-Spectral-Temporal Neural Network (SSTNN) crop yield prediction deep learning architecture. This design takes use of the complimentary characteristics of three-dimensional convolutional and recurrent neural networks. To mine temporal relationships from lengthy time-series photos, the spatial-spectral feature learning module is chained on top of the temporal dependency capture module. To eliminate the detrimental effects of crop yield label dispersion, the authors create a new loss function.

Sungha Ju et al. [110], evaluated seven of the most popular machine learning approaches on three crops using the same input variables. Six time-series scenarios, each based on data from April to September, were tested for their ability to produce accurate forecasts over a 14-year period. The time-series data includes Moderate resolution imaging spectroradiometer (MODIS) vegetation indices, agricultural production figures, meteorological data, and a county-level land cover map with 16-day-aggregated temporal resolution.

Vasit Sagan et al. [111] made use of four WV-3 photos and twenty-five PS images that were acquired during the growth season of soybean. Both a two-dimensional and a three-dimensional level of convolution neural network (CNN) designs were built. These CNN designs utilised spectral, spatial, and temporal information that was discovered in satellite data.

Dania Batool et al. [112] utilized the Food and Agriculture Organization (FAO) AquaCrop simulation model and other machine learning methods to analyse tea production forecasting methods.

Patryk Hara et al. [113] identified and analysed the independent variables most often used in artificial neural network(ANNs)based agricultural crop production prediction modelling. The paper emphasises how remote sensing and photogrammetry enable precision agriculture.

Ekaansh Khosla et al. [114] focused on the forecasting of kharif crops in the Visakhapatnam district of Andhra Pradesh, which is one of the state's main coastal districts. Modular artificial neural networks (MANNs) are used to predict monsoon rainfall. Next, they use rainfall data and crop area to anticipate main kharif crop yields using support vector regression. The quantity of agricultural output during the kharif season is mostly determined by the amount of rainfall that occurred during that season. The MANNs-SVR approach allows for the development of effective agricultural methods, which can then be used to boost the overall production of the crops.

Yan Li et al. [115] Provided Midwest US rain-fed corn yield statistics modelling. In-depth diagnostic analysis was used to explore rain-fed corn production difficulties.

Dhivya Elavarasan et al. [116] developed a yield prediction model by using DBN in conjunction with FNN. DBN with FNN resolves the issues of nonlinearity and gradient diffusion. The recommended model begins by carrying out an efficient pre-training procedure that was established by DBN. This is done in order to assist enhanced model construction and feature vector creation. In order to carry out additional processing on the typical feature vector, the FNN takes it as an input and receives it in the form of a feature vector.

Ayush Shah et al. [117] provided an intelligent method for predicting crop yield and recommending the climatic factors that will produce the highest possible crop yield. As a result of technological advances, the focus has shifted away from manually performing processes to machines and control systems processing to achieve maximum productivity.

Preeti Tiwari et al. [118] centred on calculating agricultural productivity using a variety of geographical characteristics such the normalised difference vegetation index.

Jie Sun et al. [119] developed a deep CNN-LSTM model to predict CONUS farm-level soybean yields. Weather data, MODIS LST and SR data, and crop growth characteristics were used to train the model. Thus, crop growth and environmental factors trained the model. Past soybean yield data labelled the model. Combining these training datasets and translating them into histogram-based tensors allowed the Google Earth Engine (GEE) to perform deep learning on them.

HoaThi Pham et al. [120] proposed a technique for comparing feature selection (FS), feature extraction (FX), as well as a combination of the two to non-feature reduction (All-F). The case study will employ VCI and TCI to develop 21 rice yield prediction models for eight Vietnamese subregions using machine learning. These models estimate land-harvested rice. Linear, SVM, DT, ANN, and Ensemble are provided.

2.6 Research Gaps

After conducting a complete study of various researches that have been carried out in the context of IoT used in Agriculture along with Semantic Web features, we found that there are some research gaps where still there is a scope of further research. The shortcomings of our conducted study are listed as follows:

- Despite the fact that numerous techniques have been established for semantic interoperability in Farm IoT devices, formal procedures for interoperability in technology as well as standard data formats are still lacking.
- The existing ontologies do not cover all the keywords and aspects needed for implementing semantic interoperability in the agriculture sector. There is a need of a comprehensive ontology for agriculture that provides an effective knowledge base that covers most of the concepts, instances, and relationships related to agricultural farms and IoT devices.
- As IoT is a rapidly growing technology, new concepts are kept on including; hence an adaptive ontology updating is required to ensure the reliability of data.
- An effective solution is needed to assist the farmers from starting to the ending stage of crop production with semantic reasoning.
- There is a scope of further improving the performance of yield prediction models by putting extra efforts, such as using additional weighted parameters, adding new loss functions, etc., to the existing models.

2.7 Summary

The most recent, most up-to-date literature review of IoT systems utilised in agriculture, IoT interoperability, current agricultural ontologies, and yield prediction is presented in this chapter. IoT interoperability in agriculture has been examined in terms of its significance, problems, and difficulties. Literature on IoT in agriculture has been presented in detail. The concept of IoT Interoperability has been discussed along with the Resource Description Format. Recent papers on agriculture ontology and crop yield prediction have been presented.

Chapter 3

Tools used for IoT System Setup in Agriculture Field

3.1Arduino

Electrical device construction may be done using the Arduino technology [121]. An open-source platform is Arduino. The most well-known of the two components is the microcontroller. The user may write computer code and further transfer it to the Arduino hardware using the integrated development environment (IDE).There is a good reason why the Arduino platform has swiftly grown to be fairly popular among those who are just beginning out in an electronics-related career. This greatly increases the accessibility of the Arduino board. The simplified C++ used by the Arduino Integrated Development Environment (IDE) makes it much simpler to master the foundations of computer programming.

Figure 3.1.1: Arduino board [122]

These people might include beginners as well as artists, designers, enthusiasts, and hackers, among others. A wide range of devices, including knobs, LEDs, motors, sound system, GPS systems, cameras, the internet, a smartphone, and a television, may all be connected to an Arduino device. These are only a few of the parts that it can talk to. Robots, arcade games, or even robotic systems that really can play video games may all be constructed using these instructions.

3.1.1Power (USB / Barrel Jack)

Each and every Arduino board must include a connection connector in order to be able to receive power from an external source. To give electrical current to the Arduino UNO, one may use either a USB connection that is connected to the computer or even a wall power supply (such as this one) that has a barrel jack just like its termination point. The USB connection is the more common method.

Additionally, the uploading of software into the Arduino uno board will be achieved via the use of the USB connection.

Pins (5V, 3.3V, GND, Analog, Digital, PWM, AREF)

Connect wire to the Arduino's pins to create a circuit. A breadboard and additional wires are often used in combination with this method. They often contain 'headers' made of black plastic that allow the user to easily put a wire right into the board. The user may do this by simply inserting the wire into the board. When anything is attached to the Arduino board, each of the many pins on the board, which are all organised into categories and labelled, performs a particular function. The Arduino board contains a wide range of pins.

- "Ground" is shortened to "GND" in the industry. On an Arduino, there's more than a GND pin, and any of those pins may be used to ground the circuit. The GND pins are labelled with the letter "G."
- 5V & 3.3V: Both pins are labelled with their respective voltages. Both of these pins have their corresponding voltages shown on the labels for them. The vast majority of Arduino's low-power components are happy to function whether supplied with either 5 or 3.3 volts as their supply of energy.
- Analog: The group of pins on the UNO that are located immediately underneath the label that reads "Analog In" are referred to as the "Analog In" cluster. On the PCB, these pins are labelled A0 through A5. These pins have the ability to convert an analogue sensor signal—such as one from a temperature sensor, for instance—into a digital value that can be read. We are able to interpret the data more precisely because to this feature.

- Digital: Digital pins are on the circuit board opposite the analogue connectors (0 through 13 on the UNO). These pins can conduct digital input and output. They may detect button presses, for instance (like powering an LED).
- Pulse-Width Modulation (PWM): Some digital pins may feature tildes (). (3, 5, 6, 9, 10, and 11 on the UNO).These pins have the possibility of functioning as ordinary digital pins, but in addition to that, they also have the potential to be used for a method known as pulse-width modulation (PWM).
- "Analog Reference" is what "AREF" is an acronym for when it's written out. This value must lie between 0 to 5 Volts, which is the acceptable range.

3.1.2 Reset Button

The Arduino, much like the first-generation Nintendo console, has a button that may be used to reset the device. The minute you press it, a transient connection will be created between the reset pin and ground. This will cause the Arduino to restart any code that was previously loaded into it. Even if the code doesn't repeat, this tool may be beneficial for testing it several times. Unlike the initial Nintendo system, trying to blow on an Arduino seldom fixes issues.

3.1.3 Power LED Indicator

The word "ON" is located to the right of a tiny LED that can be seen on the circuit board. This LED is below and right of "UNO" in the picture. If this light doesn't work, something's wrong. This is a rather significant likelihood. It is now time to take a second look at the circuit.

3.1.4 TX RX LEDs

"TX" is the acronym that is used to refer to "transmit," while "RX" is the abbreviation that is used to refer to "receive." These labels, which serve the goal of identifying the pins that are responsible for serial communication, are quite frequent in electrical components and serve the function of doing so. The TX and RX symbols on our Arduino UNO may be found via the digital pins 0 and 1 and by the indication LEDs. These places share a board side.

3.1.5 Main IC

An integrated circuit, most often referred to as an IC due to its leg-like shape and black colour, may be recognised by these two characteristics. Imagine it as the core of our Arduino's central processing unit. The principal integrated circuit (IC) on an Arduino may differ significantly from one board type to another; nevertheless, it nearly always originates from ATMEL's ATmega family of ICs. This family of ICs is created by ATMEL.

3.1.6 Voltage Regulator

The voltage regulator regulates Arduino board voltage. In other words, it does exactly what its name suggests. Imagine it as a type of gatekeeper that will prevent any excess voltage that may be damaging to the circuit from entering. It will do this by preventing any more voltage from entering.

3.1.7 The Arduino Family

Arduino produces several different types of boards, each of which comes with its own unique set of capabilities and features. In addition to this, the fact that Arduino boards are built on open source hardware signifies that people have the capability to change them and build derivatives of them that give even more functionality and form factors than the originals.

3.2 Temperature and humidity sensor with Arduino

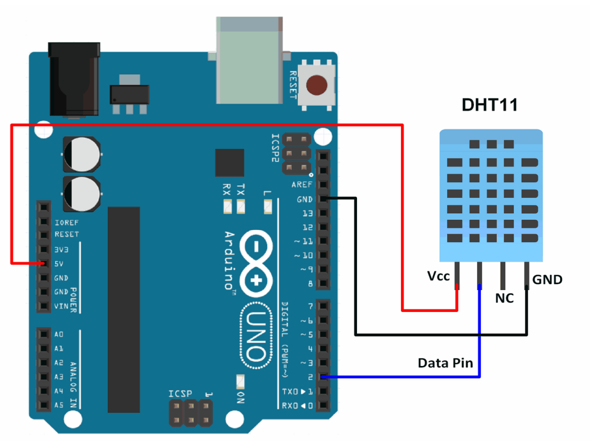

Figure 3.2.1: Temperature and humidity sensor with Arduino [123]

DHT-11 provides temperature and humidity readings via a single wire that is referred to as Data [124]. The power supply pin, also known as the VCC pin, is able to accept connections in the range of 3.5 to 5 volts.

Figure 3.2.2: Temperature and humidity sensor [125]

• Make the connection between the GND pin on the Arduino board and the GND pin on the Arduino board.

• Finally, attach a wire with a voltage of 5 volts to the VCC pin.

• And then make the connection between the Data Pin of the DHT-11 Sensor and the pin number 2 on the Arduino board.

3.3 Soil moisture sensor with Arduino

The Sensor for soil moisture is the most crucial component. The main Sensor and Control Board make it up. The Sensor for Soil Moisture uses conductive probes to measure soil water volume [126]. Several methods can measure this.

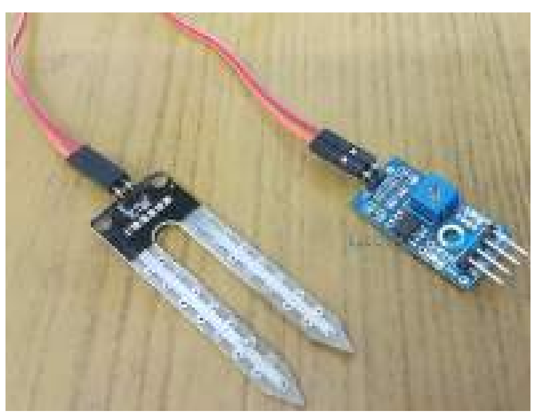

Figure 3.3.1: Soil moisture sensor [127]

3.3.1 Working of Soil Moisture Sensor

The Sensor for soil moisture has a relatively simple method of operation. The comparison of voltages is the driving force behind its operation. The following circuit diagram shows a general idea of how a soil moisture sensor operates.

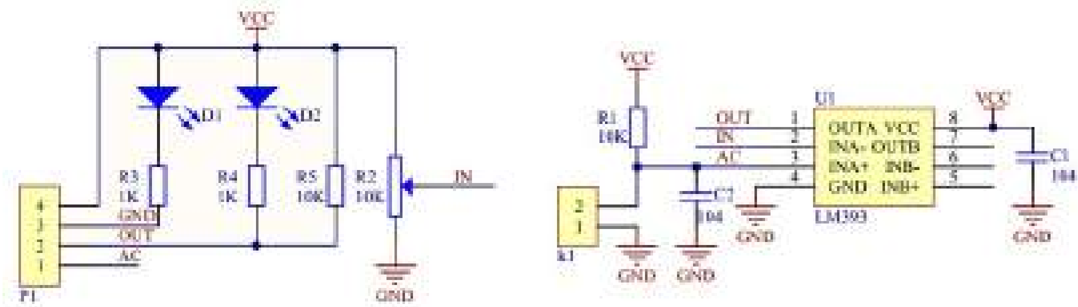

Figure 3.3.1.1: Soil Moisture Sensor working [128]

The comparator's inputs are connected to a 10K Potentiometer and a voltage divider network with a 10K Resistor and the Soil Moisture Probe. Comparator outputs link both inputs.

The probe's conductivity depends on soil moisture. The comparator's input will be greater if the probe's conductivity is lower due to reduced water concentration. The comparator output is HIGH, hence the LED will not light.

3.3.2 Interfacing Soil Moisture Sensor with Arduino

The soil moisture module has digital and analogue outputs, its main utility. This analogue signal may be sent into the Arduino's Analog IN port to correctly assess soil moisture.

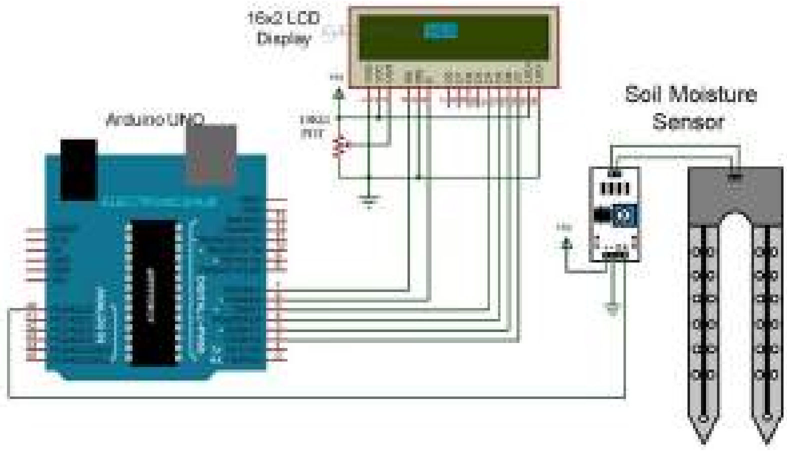

Figure 3.3.2.1: Soil Moisture Sensor interfacing with Arduino [129]

3.4 Soil pH Sensor with Arduino

The term "pH sensor" refers to the instrument that measures the amount of hydrogen ions (H+) present in a liquid. The acidity or alkalinity of a liquid may be determined from this. When a pH sensor is submerged in a liquid solution, smaller ions are able to pass through the boundary area of the glass membrane and into the solution below, while larger ions are retained in the liquid. The voltage difference between the electrodes is what the pH meter monitors.

3.4.1 Working of pH meter

The pH meter consists of a module and a pH electrode. The module features a voltage regulator that can handle power supplies ranging from 3.3v to 5.5v DC. Some models have a 5v DC that is compatible with a wide variety of programmable boards, including Arduino, ESP 8266, STM, and ESP 32. A module that has circuitry that can output filtered signals with reduced jitter is called a filtered signal output module. A potentiometer that can calibrate the pH electrode is also included in the module [130].

3.4.2 pH Electrode probe working

Glass and non-glass electrodes exist. Thus, a glass electrode's pH sensor element is a glass bulb at the tube's end. This glass tube electrode contains a silver chloride-coated silver wire and a pH-7 potassium chloride solution. Structural diagrams are shown below.

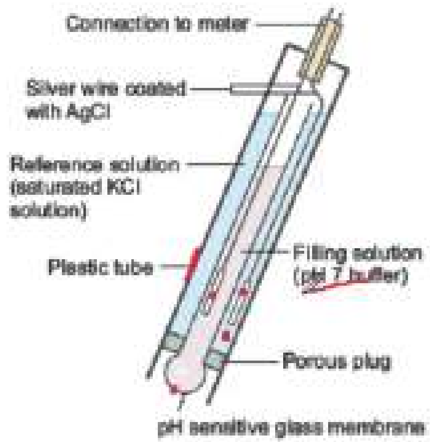

Figure 3.4.2.1: Working of pH Electrode probe [131]

The reference system, which is located on the exterior of the glass or plastic tube as shown in the picture, is also composed of silver chloride that is coated on silver wire and immersed in a potassium chloride solution that is entirely saturated. This can be seen in the image. There is no difference in potential between the two different solutions since it is known that both the solution at the glass electrode and the solution at the reference electrode have the same pH. The porous plug isolates the reference system from the medium that is going to be measured while yet allowing the electrical connection that links the two systems together to remain intact. Calculating the pH value requires taking the potential difference between the reference system and the measuring system into account, and this is done by measurement.

The positively charged H+ ions from the solution travel towards the surface of the glass membrane when the glass is dipped into the solution to be measured. The same process occurs with the internal solution, which moves the H+ ions towards the glass membrane inside. Now, the most essential component of the probe is the pH-sensitive glass membrane, which has been meticulously crafted in such a manner that the H+ ions migrate to the surface of the glass membrane and bind to it. This is the most crucial aspect of the probe. This is due to the pH sensitive glass membrane having a change in potential, which is induced by a difference in the amount of H+ ions that are present on both sides of the membrane. This potential difference will be captured by the signal conversion module, and then the Nernst equation will be used to calculate the pH value. The module's responsibility lies in this process.

3.4.3 Interfacing Soil pH Sensor with Arduino

If the concentration of hydrogen ions on the inside of the container is lower than the concentration on the outside of the container, then the measured solution is acidic, and the pH value is less than 7. On the other hand, if the concentration of H+ ions on the inside of the container is higher than the concentration on the outside of the container, then the measured solution is basic, and the pH value will be greater than 7. As can be seen in the diagram below, the output of the pH sensor is linked to the analogue read input on the Arduino board. The pH sensor generates a variety of analogue outputs, each of which is specific to the liquid solution being measured. It is simple to calculate the pH value of other liquid solutions if one is familiar with the value of a recognised solution, such as water.

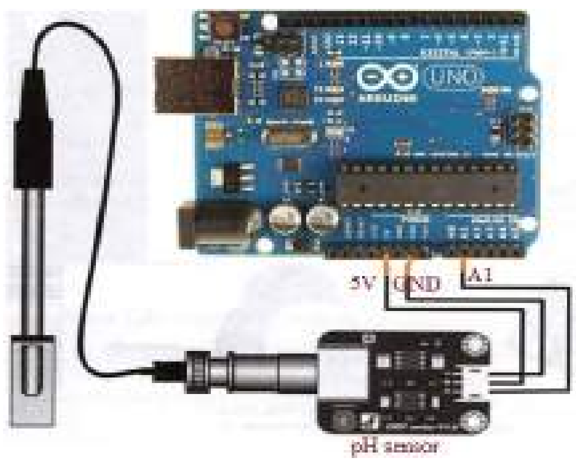

Figure 3.4.3.1: Soil pH Sensor interfacing with Arduino [132]

pH sensor-Arduino board connectors are below.

Vcc (+ pH sensor pin) - 5V (Arduino side)

GND (-pH sensor side pin) (Arduino side)

OUT (pH sensor pin) - A1 (Arduino side)

3.5 Interfacing light Sensor with Arduino

LDRs which stand for light dependent resistors are also referred to as photo-resistors because of their sensitivity to light. Photo-resistors are utilised to provide an indication of either the presence or absence of light in a given environment. The photo-resistor's resistance goes up when there is not enough light, but it goes down dramatically when there is enough light.

Figure 3.5.1: LDR light dependent resistor [133]

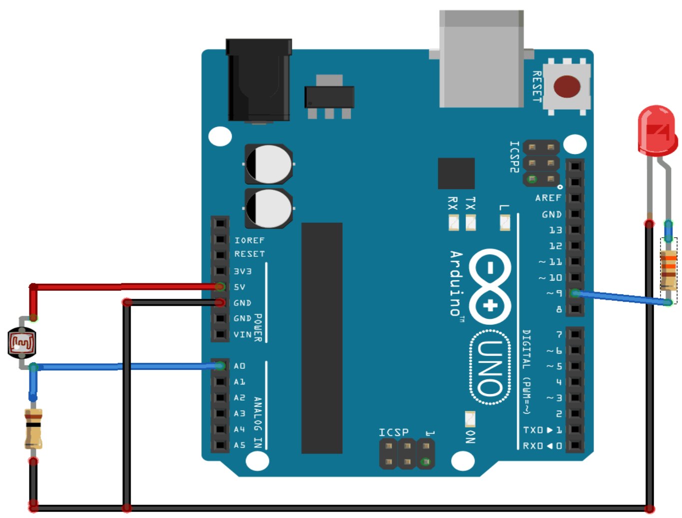

Figure 3.5.2: Light sensor interfacing with Arduino [134]

LDR is a component that has two terminals. Terminal one is the signal pin, which has to be connected for the proper working of code. Another terminal is believed to be the ground pin, and it is expected that this pin will be linked to the system's ground. The LDR SENSOR outputs low when there is no lighting and high when light is focused to it.

3.6 ThingSpeak Cloud Framework

A conventional IoT system links "things" with an Internet of Things service. One fascinating result of the IoT systems' "things" is that they cannot function without connecting to other "things." The entire potential of the Internet of Items is revealed when individual items connect to a "service," either directly or indirectly via other "things." In these systems, the service acts as an invisible manager, providing everything from data collection and monitoring to complex data analysis. This graphic shows where an Internet of Things service fits in an ecosystem.

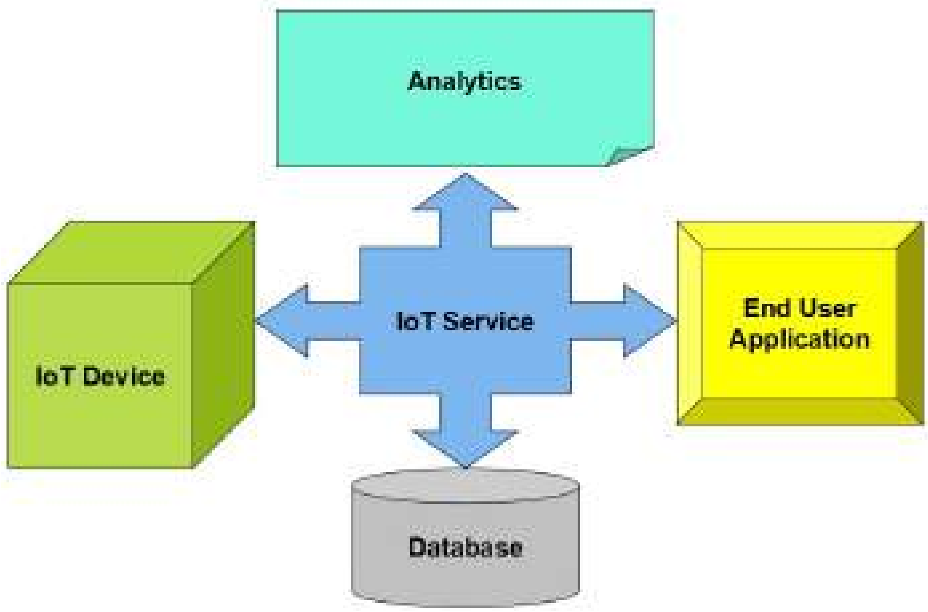

Figure 3.6.1: ThingSpeak framework [135]

ThingSpeak provides services for developing Internet of Things apps. It collects real-time data, visualises it in charts, and lets you build plugins and apps for web services, social networks, as well as APIs. ThingSpeak's core is a "ThingSpeak Channel." Channels store ThingSpeak data and consist of the following:

- Eight fields for storing any sort of data from a sensor or embedded device.
- There are three location fields that may be used to record the coordinates for the place, including the latitude, longitude, and elevation. These are really helpful when attempting to keep track of a moving object.

- There is one status field, which contains a brief message that describes the data that is being saved in the channel.

Signing up for ThingSpeak and establishing a channel are both prerequisites for using the platform. After we have a channel, we will be able to submit the data, give it to ThingSpeak to process, and then get the data once it has been processed. Let's begin our investigation into ThingSpeak by creating an account and a channel for ourselves.

3.7 Angular

TypeScript is the foundation upon which the Angular development platform was constructed. As a platform, Angular contains the following components:

- A framework that is built on components for the construction of scalable web applications.
- A grouping of properly integrated libraries that perform a wide variety of tasks.
- A collection of tools for developers that may assist in the process of developing, building, testing, and updating code.

Angular was created to make it as simple as possible to implement updates, allowing users to benefit from the most recent innovations with the least amount of work feasible.

Developing Angular apps using the Angular Command Line Interface (CLI) is the method that is considered to be the quickest, simplest and most recommended method. The Angular Command Line Interface (CLI) simplifies a variety of operations. Here are several examples:

- **ng build**: Creates an output directory containing a compiled version of an Angular app.
- **ng serve** will create and serve your application, automatically rebuilding itself whenever a file is modified.
- **ng generate:** Creates new files or edits existing ones based on a schematic.
- **ng test**: Performs unit testing on the specified project.

- **ng e2e**will build and serve an Angular application before carrying out end-to-end testing on the application.

3.7.1 Prerequisites

Node.js: Node.js must run at its most recent supported version for Angular to work properly. Check the engine key in the package.json file for more information on the exact version requirements. Visit nodejs.org for more details on how to set up Node.js on your computer. In order to determine the version of Node.js that is installed on computer, "node -v" command is used.

npmpackage manager: Many of the features and capabilities of Angular, the Angular Command Line Interface (CLI), and Angular apps are dependent on npm packages. You will need an npm package manager to download and install npm packages. • A grouping of properly integrated libraries that perform a wide variety of tasks, including client-server communication, routing, as well as form management. Run the command npm -v in a terminal window to determine whether or not the npm client has been installed on your computer.

The src/app directory contains all of the application source files. The following is a list of important files that are automatically generated by the CLI:

- **app.module.ts** is the file that details the files that are used by the program. This file coordinates the activities of the other files included inside your program and serves as a central command center.
- **app.component.ts**, which is sometimes referred to as the class, is the file that stores the application's logic for the main page.
- **app.component.html** is the file that stores the HTML code for the AppComponent. The information included inside this file is sometimes referred to as the template. The view, or whatever is shown in the browser, is determined by the template.
- **app.component.css** is the file that stores the styling for the AppComponent component. When you wish to specify styles that are particular to a single component, as opposed to the styles that apply to your application as a whole, you will use this file.

3.8 Summary

The hardware and Software requirements for an IoT System Setup in the Agriculture field have been presented in this chapter. Arduino is a platform which is used in designing and developing IoT systems. The Arduino board and its components are explained in detail. The operation of IoT devices, including soil moisture sensors, humidity and temperature sensors, light sensors, and ph sensors, as well as their interface with Arduino, is detailed along with a list of each one's unique properties. A brief discussion of an IoT analytical platform, “ThingSpeak,” is provided, which is used for aggregating, analyzing, and visualizing the sensors' generated data in Cloud. Angular is an open source platform which is widely used in developing web applications; an explanation of the Angular platform and its components is given in detail.

Chapter 4
Proposed Methodology

As a result of recent developments in the Internet of Things, it is now viable to manage a tremendous number of sensor data streams by using a range of different large-scale Internet of Things platforms. This was previously not possible (IoT). Recent technical developments have made this feasible. Real-time data streams are gathered, analysed, and evaluated using these Internet of Things frameworks [136]. Additionally, they enable the provision of clever solutions intended to facilitate the decision-making process. The great majority of Internet of Things-based products now available on the market are domain-specific, offering stream processing and analytics tailored to certain sectors. The food supply chain is significantly impacted by a wide variety of external factors that are relevant to many other industries in the context of the agri-food industry [137–138]. These criteria include things like rules and weather conditions. However, in order to fully realise the concept of smart farming, frameworks for the internet of things that are both adaptable and versatile are still lacking.

4.1 Proposed Framework

The framework proposed for the development of an effective semantic knowledge base for IoT used in agriculture is shown in figure 4.1.2; it provides a complete structure of the entire process from crop selection to yield prediction. To achieve the defined objectives, the research work has been divided systematically into three phases: crop selection, ontology development and crop monitoring, yield prediction.

- **Phase 1: Crop selection**
  - Gather data from the user: soil type, soil components, season, month etc.
  - Build a model to predict the best crop.
- **Phase 2: Agriculture IoT ontology development and IoT based crop monitoring**

Develop ontology for IoT devices used in agriculture, Collect real-time data from sensors and different users.

- **Phase 3: Yield Prediction**

The data gathered is processed by Machine Learning algorithms.

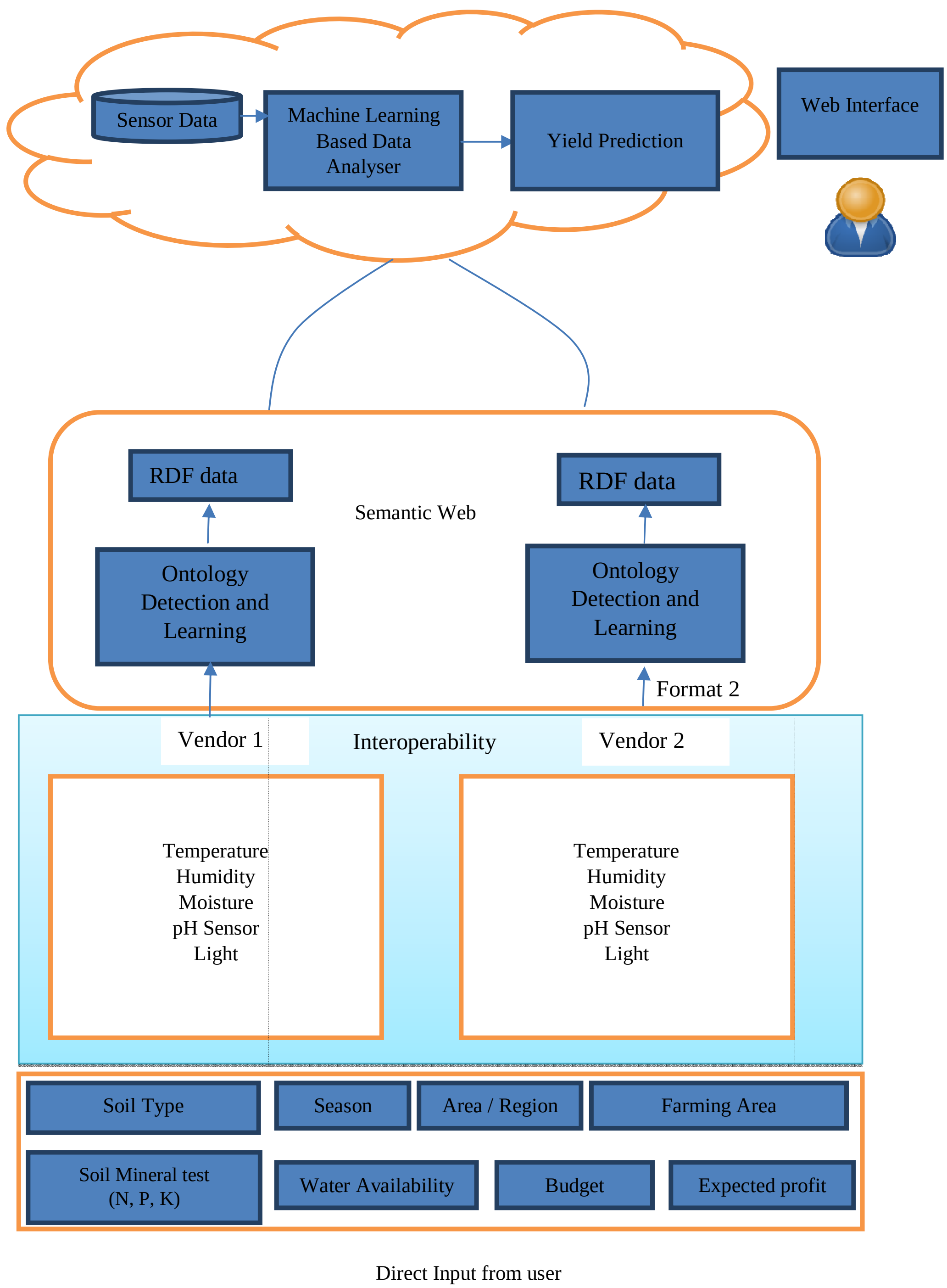

Figure 4.1.1: Proposed Framework

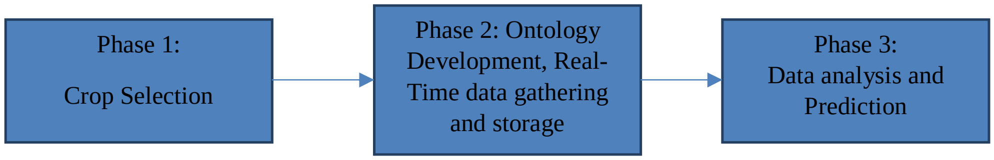

Figure 4.1.2: Proposed Approach

4.2 Crop Selection

One aspect of our daily life that has a big impact on food production is agriculture. Farming is the primary means through which food is produced. Food production is being negatively impacted by a wide variety of issues. Good crop selection is one of the primary strategies that may be used to alleviate the issues that are plaguing farmers [139]. We built a model of crop selection using IoT that assists farmers in selecting the most suitable crop for their farms. This model was created for their benefit.

There are wide varieties of plants, each of which has specific requirements for their growth such as, the kind of soil, the types and quantities of nutrients, and the type of water supply and amount of water [140]. The growth season and the environment of the location in which the plant is cultivated are other factors that influence the quantity of water that the plant requires. If the right crop is produced on the soil and in the environment most conducive to its efficient development, it will be feasible to maximise harvests and decrease the quantity of water required for irrigation.

The choice of crops to grow is the single most critical factor in successful crop farming. The following are some important considerations to address while choosing crops: the location of the farm, the availability of land, the kind of soil, the climate, and the amount of money you invest in the farm and how much you want to receive back, all of these things are important considerations. Demand in the market, availability and quality of water, individual concerns etc., are other factors that will affect crop growth. The parameters that are considered for the crop selection process are further discussed in detail as follows:

- **Soil Type:** The organic and inorganic substances that are found on the surface of the ground are referred to as soil. Soil type is one of the major factors, as it acts as the natural medium for plant development. There are different types of soils, such as Sandy, Silty, Clay, Peaty, Chalky, Loamy etc., and each of them has its own properties and features that will help in the rapid growth of crops if the specific crops are cultivated in specific soil type which is best suitable to them.

- **Soil Nutrient Test:** The Soil nutrient test is an essential test that takes readings of the levels of nitrogen (N), phosphorus (P), and potassium (K) minerals in the soil in order to forecast potential plant productivity accurately. The nutrient test should be conducted before crop cultivation in order to determine whether the soil is capable of meeting the nutrient requirements of the crop.

- **Geographical Factors Influencing Agriculture (Area/ Region):** Agriculture is impacted by a number of geographical factors:
    - Natural Factors
    - Economic Factors
    - Social Factors
    - Political Factors

  The expansion and growth of agriculture are always guided and governed by a variety of elements, including physical, economic, social, and political aspects. It is important for the farmers to be aware of these factors in the particular area where they are planning to grow so that they can choose the right crop to grow. Choosing the right crop for every agricultural field is a key to high crop growth and yield.

- Season, water availability, water supply sources, labour availability and equipment are other additional factors that are essential for the crop selection process.

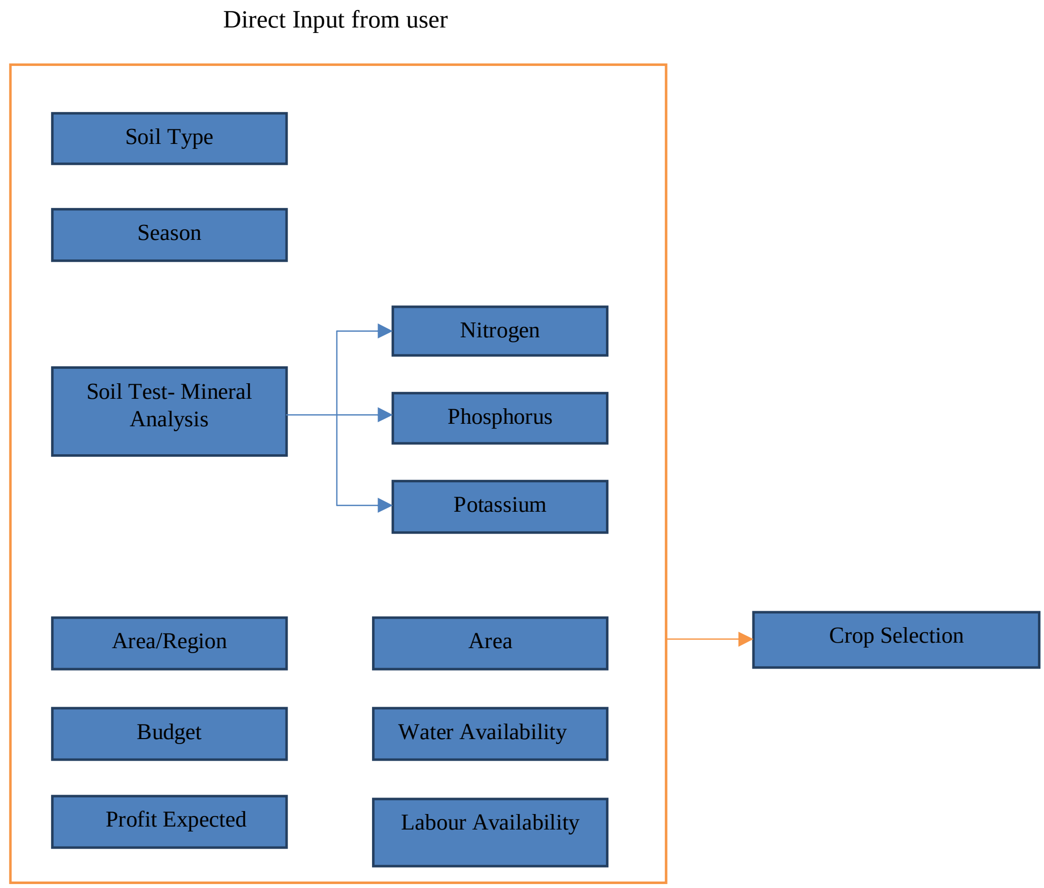

Figure 4.2.1: Crop selection criteria

4.2.1 KNN Algorithm for Crop Selection

The KNN technique is often used to classification and regression issues. In the training stage, it stores all the data, and whenever a new data point is encountered, it checks the similar features of the data with the already stored data and categorised it accordingly. The close proximity is estimated by using standard distance functions Euclidean Distance, Taxicab Distance, Minkowski Distance, and Hamming Distance etc.; In the Crop selection process, the KNN algorithm will be applied to predict the crop which is best suitable for the given conditions. The input is gathered from the farmer, and by considering the essential parameters, soil type, season, month etc., the Euclidean distance is calculated for K nearest neighbours, and the best suitable crop is suggested.

The standard conditions for an ideal crop growth are shown in the following table.

Table 4.2.1.1: Requirements of crops

S. No.	Crop	Soil type	Season	Month	N Kg/Hectare	P Kg/Hectare	K Kg/Hectare
1	Potato	2,6	2	1,10	240	90	130
	Tomato	1,2	2, 1	11,7	200	250	200
3	Cotton	2,3	1	4,6	250	181	181
4	Ground Nut	2,6	1	6	112	27	34
5	Wheat	1,6	2	12	40	30	30
6	Maize	1,6	1,3	3,6	100	30	7
7	Sorghum	1	1	6	90	45	45
8	Sugar cane	6	4	9	300	100	100
9	Chili	6	2,4	1,9	100	50	50
10	Paddy rice	1	2,1	6,11	150	50	60

Soil type: 1 – Clay, 2 – Sandy, 3-Silty, 4-Peaty, 5-Chalky, 6-Loamy.

Season: 1-Summer 2-Winter 3-Spring 4-Rainy.

Months: 1-12.

4.3 Agriculture Ontology Development and IoT based crop monitoring

The Internet of Things not only reduces farmers' excessive the use resources like water and power but also helps them save time. The enhanced interconnectivity and sensor technologies made available by IoT in the agriculture industry are directly responsible for these advantages. Using IoT sensors that collect data on the present state of agricultural growth, the status of crops may be kept track of at any time. Predictive analytics will be made possible by the Internet of Things with agriculture in the future, enabling farmers to make better harvesting decisions.

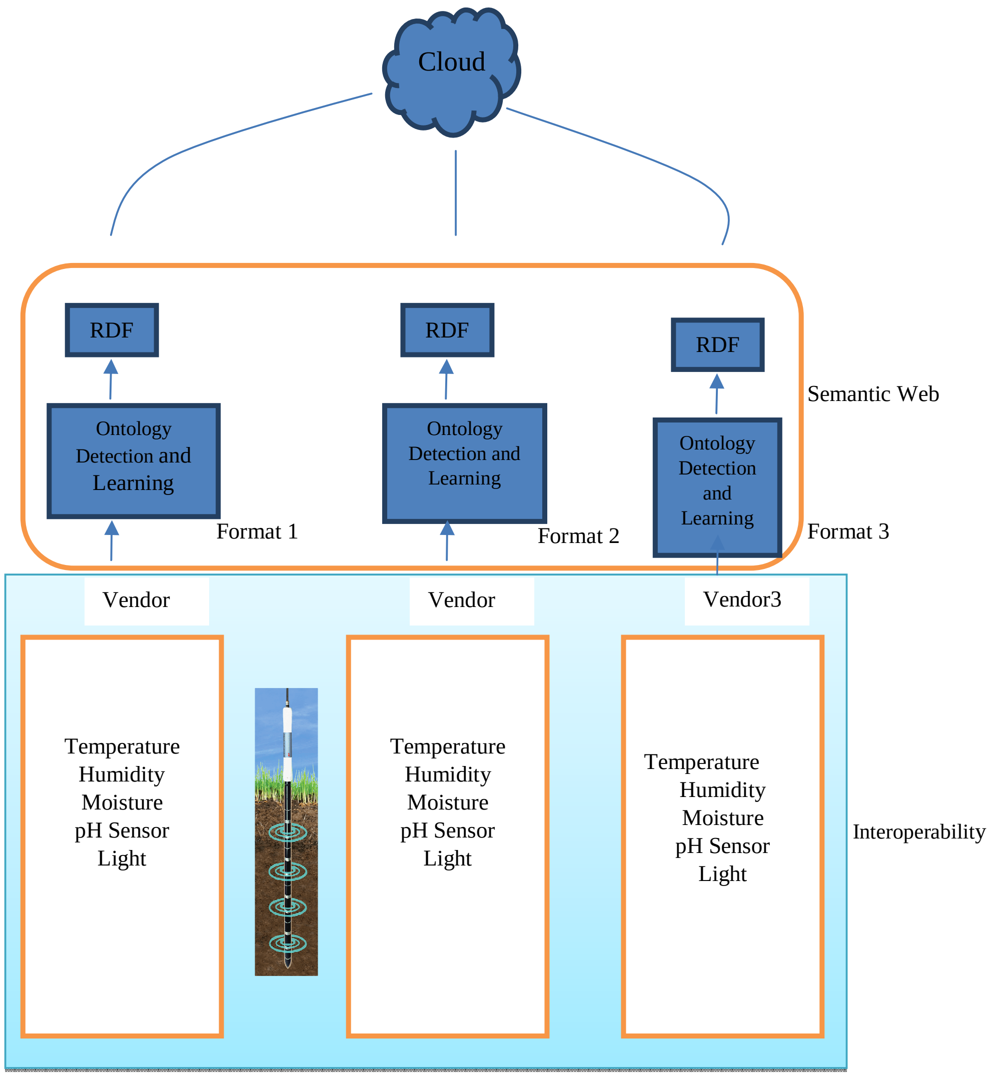

Figure 4.3.1: Data collection and upload

Massive volumes of heterogeneous data are generated as a consequence of the utilisation of Internet of Things devices, and this data provides insightful information. Numerous studies have been conducted in an effort to turn this data into knowledge and information that may be useful. The ontology for the IoT devices used in agriculture has been created using OWL-RDF. The metadata may be transferred across IoT devices in a meaningful and trustworthy way by using the created ontology. The information that can be learned from the data acquired about the various environmental variables is what eventually helps with the system monitoring.

The steps involved in this phase include:

1. An effective knowledge base through an agriculture ontology has been developed that includes all the classes, taxonomies and relations involved in the agriculture domain.
2. Ontology update algorithms are built to update the ontology whenever a new tag encounters.
3. Data from sensors will be gathered, and the meaning of the data will be determined by parsing it using the created ontology.

4.3.1 RDF working

RDF (Resource Description Framework) is a standardised method for making claims about resources. The availability of an open as well as interoperable standard for the interchange of data and metadata is necessary for the semantic web. This is exactly what RDF offers, which is why it was first standardised in the first place.

A triple is the collective noun for the following three parts that make up an RDF statement:

1. The triple is using the subject, which is a resource, to describe something else.
2. The predicate provides an explanation of the connection that exists between the subject and the object.
3. A resource that is connected to the topic is referred to as an object.

Both the subject and the object are nodes that stand in for certain items. Because it illustrates the connection that exists between the nodes, the predicate is in the form of an arc.

There are three distinct varieties of nodes that are allowed under the RDF standard. These nodes are as follows:

- A unified resource identifier, or URI, is a system that has been established for identifying resources, whether those resources are tangible or intangible. The URI format's subtype, the Uniform Resource Locator (URL), is often used in RDF assertions. The Internationalized Resource Identifier (IRI) was added as a new node type by the World Wide Web Consortium (W3C) as part of the RDF specification update that took it to version 1.1 in 2014. IRIs, which function in concert with URIs to enable the use of international character sets, are extremely similar to URIs.

- A literal is a specific data value, which might take the form of text, a date, or a number. It may also take the form of a time-related value. When literal values must be sent, the URI or IRI format is used.
- Another name for a blank node identity is an anonymous source of information or a bnode. There are several names for these words, such as: It is a symbol for a subject about which nothing is known but the connection between the two. An exclusive syntax is needed to distinguish blank node IDs.

4.3.2 Proposed RDF model for Ontology Development

An XML/RDF file constructs the OWL ontology using JSON triples in an OWL-RDF. Reverse mapping is used to parse OWL-RDF into abstract syntax. In those particular triples that determine the class definitions and properties, it's essential that the reverse mapping should not be unique.

Class (a)

Class (b)

SubClassOf (b a)

and

Class (a)

Class (b partial a)

Under mapping, both results in the same collection of triples:

a rdf:typeowl:Class

b rdf:typeowl:Class

b rdfs:subClassOf a

For different purposes, this is not a problem, like species validation. In other cases, the strategy includes the consistent parser. Here, the abstract syntax descriptions generate by using the editing tool.

DL and OWL Lite may not be connected to an RDF graph. DL ontology and OWL Lite mapping may transform or generate the graph. A species validator computes ontology existence, and a parser establishes it. In two different ways, the correspondence of an OWL ontology towards the RDF graph may cause failure:

1. The mapping of the triples' superset is allowed by DL ontology or an OWL Lite in the abstract syntax. Some of these triples have forgotten or not available in the graph.

2. The triples or superset of triples mapping is there in the format of abstract syntax in the ontologies. Some limitations are violated for membership of Lite subspecies or the OWL DL. This is the case for non-availability of such kind of ontologies.

4.3.3 Parser Implementation

During the parsing, file processing is encountered incrementally, which follows a streaming fashion by most of the XML parsers reporting the elements to the parser. From an RDF or an XML, it's difficult to perform the process or a task like producing an OWL ontology while RDF models are parsed. In processing the graph by triples, the order is not ensured, which causes the problem and reports the streaming sparser. The syntax with a particular construct may categorize across different locations in the RDF file.

The parser waits until all triples are accessible. If triples are gathered and processed, a parser's conceptual complexity is lowered even while data is streamed. Ramifications take resources when parsing. Memory is needed to parse huge RDF graphs.

The developed ontology will be saved as an OWL file, which in turn directly cannot be used in web applications; for this, it must be converted to JSON format. The user provides the owl file to be modified. The conversion from OWL file to JSON file is performed by using the procedure shown in Algorithm 1.

Algorithm 1: Owl file to Json string conversion

Input: Owl file

Output: Json file

Step 1: Get the Owl file.

Step 2: Read the owl file and extract the information in the form of a string (referred as *Owl data string*).

Step 3: Using Ontology search algorithm, find the <*Declaration*> tags in the Owl file and extract the keywords.

Step 4: Using Ontology Tag search algorithm, find the <*SubClassOf*> tags in the Owl file and extract:

- Sensor keywords
- Alternative names for the sensors

Step 5: Write the data into a json file.

Algorithm 1 presented the procedure to convert an OWL file to JSON string. The data from the OWL file is read into an *owl data string*. The algorithm is designed based on the structure of the data present in the *owl data string*. The tags of <*Declaration*> and <*SubClassOf*>are extracted using the Tag search algorithm presented in algorithm 2. This helps in extracting the sensor keywords and their alternate names.

Algorithm 2: Ontology Tag search algorithm

Input: Owl data string, tags: <*SubClassOf*>, </*SubClassOf*>

Output: Sensor keywords and the corresponding linked alternative keywords

Step 1: find the positions of tags <*SubClassOf*>, </*SubClassOf*> in the Owl data string. Let the positions be *pos1* and *pos2* respectively.

Step 2: Extract the string data present between *pos1* and *pos2*. Let the substring be called as *OwlSubString*.

Step 3: Find the positions of double quote (“) in the *OwlSubString*. Let the positions be called as *pos_21, pos_22, pos_23, pos_24.* Here *pos_21* and *pos_22* corresponds to the position of the sensor. *pos_23* and *pos_24* represent the position of the alternative sensor name in the *OwlSubString*.

Step 4: Obtain the sensor keyword and the alternative name of the sensor.

Step 5: Store the information in a structure.

Algorithm 2 presented the ontology tag search procedure. The algorithm is focused on finding the <*SubClassOf*>, </*SubClassOf*> tags form the input string. Based on the positions of the tags, the data present between the tags is extracted. For instance, from the tag shown below:

<SubClassOf>

<Class IRI="#T"/>

<Class IRI="#Temperature"/>

</SubClassOf>

The <*SubClassOf*> tag has two fields, first one for the sensor name and the second name for the alternative name. The algorithm thus searches for the double quotes in the text to identify these two fields and extracts them. The result of the Algorithm 2 on the above data is:

Sensor Name: Temperature

Alternate Name: T.

Once all the tags are extracted, parsing of the OWL is complete. This information is saved in the form of a JSON string. The next step is to update the string to produce the updated OWL file and JSON file. This procedure is discussed in algorithm 3.

Algorithm 3: Owl File and Json File updation

Input: New alternative words for sensors

Output: Updated Owl file and Json File

Step 1: The user selects the sensor name to which alternate name is to be added.

Step 2: Read the sensor name and the alternative name form the text box provided in the form.

Step 3: create the <*Declaration*> tag for the alternative name and insert it into the Owl data string

Step 4: create the <*SubClassOf*> with the sensor name and alternative name and insert it into the Owl data string.

Step 5: write the data into json file and owl file.

Algorithm 3 presents the procedure to add new alternative names to the sensors. This can be achieved by adding the <*Declaration*>and <*SubClassOf*>tags for the new alternatives.

4.4 Crop yield prediction

Predicting crop yields is a major agricultural difficulty. It influences global, regional, and local decisions. Agricultural production forecasts involve soil, climate, environment, and crops. Decision support algorithms often extract crop attributes for prediction. Precision agriculture emphasises monitoring, management information systems, variable rate technologies, and cropping system variability. Precision agriculture improves agricultural yields, quality, and environmental impact. Simulations of agricultural production may help explain the cumulative effects of water and nutrient deficiencies, pests and diseases, crop yield variability, and other growing season variables.

Farming relies on yield forecast for agricultural marketing. Early yield prediction helps farmers modify crop growing conditions to increase output. We created a yield prediction algorithm that parses sensor data using our ontology and predicts crop production. Weighted linear regression predicts yield. More accurate agricultural output data may improve economic choices and profitability.

4.4.1 Linear regression

The basis of the machine learning algorithm known as Linear Regression is gained via the process of supervised learning. It is responsible for carrying out a job that involves regressing. Regression, which is founded on independent variables, enables one to model a value for goal prediction that can be modelled. The majority of the time, it is used in establishing how the variables are related to one another and in producing forecasts. In addition to this, it can be used to make predictions about dependent variables by basing those predictions on one or more independent variables.

Simple Linear Regression Formula:

$$y = \theta_1 + \theta_2 \,.\, x \quad \text{or} \quad y = mx + c$$

One goal of the method known as linear regression is to examine a response variable Y that fluctuates according to the magnitude of an intervention variable X. The word "prediction" refers to a technique wherein the value of an explanatory variable which has previously been established is used to estimate the value of a response variable. The most common kind of linear regression is the least-squares fit, which may be used to represent both linear and polynomial relationships. Additionally, it may be used to simulate nonlinear interactions. Adapting estimations to values beyond the initial data set from where they were produced is a process known as extrapolation. The following procedures are used to achieve linear regression:

- The model has linearity, essentially normal residuals, and constant variability. Since we are employing a linear model for prediction, linearity requires a linear relationship between the response variable and the explanatory variable. The notion of nearly normal residuals predicts a residual distribution centred around. There are various instances when unusual discoveries may deviate from the data's trend. A histogram or residual probability map may immediately confirm this condition. The residuals are regularly distributed if the histogram is symmetric. If residual plots are closer to normality, symmetry is met.

- Calculate the residual values, which are essentially leftovers from the calculated model fit.
- Get the R^2 value after doing the Residual Sum of Squares calculation. The sum of the squares that indicate the difference between the predicted and observed values is the definition of the residual sum of squares. It might be described as a discrepancy between the data and an estimating model. $R^2$is the square of the correlation coefficient, which can be found in most statistical software, to put it another way. The most used statistic for evaluating the reliability of linear models is R^2. The proportion of variance in the response variable is shown by the R^2value. The degree of variation in the response variable that is assigned to the model is represented by the value of R^2, which is never more than 1. R^2's value is always in the range between 0 and 1. One variable is considered the response variable, while another is considered the explanatory variable for determining the R^2value. This creates a continuous linear relationship between the variables. The linear regression is presented as:

$$y_i = \mathbf{x}_i^{\mathrm{T}} \mathbf{w} + e_i$$

where y is the response variable, **x** is the feature vector that has (n+1) x1 dimensions, **w** is the vector that contains the regression coefficients that has (n+1) x1 dimensions, and e is the observation error. Take note that the first component of vector **x** has a value of 1, which stands for the interception (or bias).

$$\mathbf{x}_i = [1, x_{i1}, x_{i2}, \ldots, x_{in}]^{\mathrm{T}}$$

The following may be used to represent the linear regression model as a matrix:

$$\mathbf{y} = \mathbf{X}\mathbf{w} + \mathbf{e}$$

where e is a m x1 vector representing observation errors, y is a m x 1 response vector, and **X** is a feature matrix with sizes of m (n+1). The coefficient of linear regression may be calculated as follows:

$$\hat{\mathbf{w}} = (\mathbf{X}^{\mathrm{T}}\mathbf{X})^{-1}\mathbf{X}^{\mathrm{T}}\mathbf{y}$$

Keep in mind that the estimate of interception is the first part of **w**.

4.4.2 Weighted Gradient Linear Regression

Weighted gradient linear regression incorporates error covariance into linear regression. Thus, heteroscedastic data may benefit. The gradient linear regression model changes slope values for various growth stages as crop needs vary. The weighted model assigns priority to the parameters for better prediction accuracy.

$$Minimize\left(\frac{w}{n}\sum_{i=1}^{n} y_i - (x_i m + c)\right)$$

y_i is the desired parameter value

x_i is the input parameter value

m, c parameters of logistic regression

w is the weight added.

The requirement for the crop keeps changing from time to time. The prediction will yield better performance when the data is divided into parts; gradient regression is applied to each part separately. The prediction is evaluated every two months, and the final prediction is made by using the weighted average function, which improves the accuracy of the prediction.

4.5 Summary

The proposed framework and the methods used in the development of a semantic knowledge base for IoT in Agriculture are presented in this chapter. The proposed framework represents the conceptual structure of the entire research work, which describes the activities and methods to be followed in order to achieve the defined objectives. This research work is carried out in three phases: crop selection, ontology development and crop monitoring, yield prediction. The methods applied in each phase, KNN algorithm, OWL-RDF, RDF statements, Linear Regression, and Weighted Linear Regression are discussed in detail.

Chapter 5

Implementation and Results

The Internet of Things is essential to smart farming, which reduces human labour and enhances yield in every aspect. The Internet of Things has enabled better water utilisation, input optimization, crop monitoring, yield prediction, and more as agriculture becomes increasingly dependent on it. An Agriculture ontology handles heterogeneous data from IoT devices in agriculture. The ontology lets the web interface extract relevant IoT data.

IoT-based smart farming improves agricultural efficiency by monitoring crops in real time. The Internet of Things has saved farmers time and reduced water and power waste. IoT's sensor technologies and interconnection in agriculture have led to these advantages. It monitors humidity, temperature, soil moisture, pH, etc. in real time. A Web Interface has been developed that assists the farmers in different stages of crop production, which provides the users with an access to the developed frameworks, Crop Selection, Crop monitoring with semantic interoperability, and Yield Prediction.

5.1 Crop Selection

One of the key determining criteria for successful crop farming that results in effective and lucrative crop production is the choice of the crop. The ideal crop must be chosen based on a variety of criteria, including the availability of resources, the kind of soil, and the weather, in order to produce a higher yield and make a profit.

The following details are collected from the user:

1. Personal Details such as name, as shown in figure 5.1.1.

Figure 5.1.1: Farmer personal information

2. Land Details of the farmer

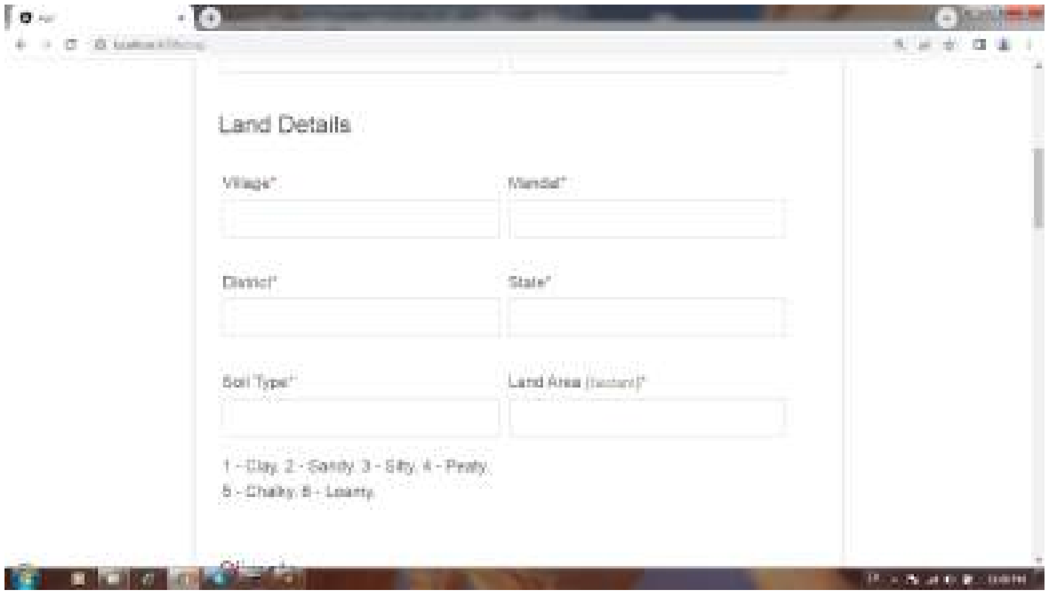

Figure 5.1.2: Land details

The land details include the following:

- Village
- Mandal
- District
- State
- Soil Type:

  1 - Clay

  2 - Sandy

  3 - Silty

  4 - Peaty

  5 - Chalky

  6 - Loamy

- Land Area (acre)*

The climate details at are collected are as follows:

Figure 5.1.3: Climatic details

The climate details include season and month of plantation.

Figure 5.1.4: Macro nutrients

The macro nutrients include

- Nitrogen
- Phosphorus
- Potassium

Based on the collected information, the crop is selected.

Table 5.1.1 Crop Selection criteria

	Soil Type	**Season**	**Month**
Cotton	Sandy	Summer	April
	Silty	Summer	June
Potato	Loamy	Winter	January

	Sandy	Winter	January
	Loamy	Winter	October
	Sandy	Winter	October
Tomato	Sandy	Winter	November
	Clay	Winter	November
	Sandy	Summer	July
	Clay	Summer	July
Groundnut	Sandy	Summer	June
	Loamy	Summer	June
Wheat	Clay	Winter	December
	Loamy	Winter	December
Maize	Clay	Spring	March
	Loamy	Spring	March
	Clay	Summer	June
	Loamy	Summer	June
Sugarcane	Loamy	Rainy	September
Chilli	Loamy	Winter	January
	Loamy	Rainy	September
Rice	Clay	Summer	June
	Clay	Winter	November

Table 5.1.2: NPK requirement Kg per acre

Crop	**Nitrogen (N)**	**Phosphorus (P)**	**Potassium (K)**
Cotton	250	181	181
Potato	240	90	130
Tomato	200	250	250
Groundnut	112	27	34
Wheat	40	30	30
Maize	100	30	7
Sugarcane	300	100	100

Chilli	100	50	50
Rice	150	50	60

KNN based crop selection

K-Nearest Neighborsis a type of supervised learning algorithm used for classification and regression. The basic idea behind the algorithm is to find the k-number of closest data points in the feature space and use them to make a prediction about the target variable for a new observation. The prediction is based on the majority vote or average of the k-nearest neighbors' target variable values. It is a simple and effective algorithm for small datasets, but it can be computationally expensive and less accurate for large datasets.

After collecting the inputs from the user, the KNN algorithm suggests the best suitable crop by evaluating the information provided. The parameters, mainly season, month, and soil type, are considered, and the crop that is in close proximity ofthese conditions is suggested.

As sample input, the details are entered as follows:

Table 5.1.3: Sample Input

Input Category	**Value**
Soil type	Silty
Land Area	1acre
Season	Summer
Month	June
Water source	Bore well
Equipment available	Yes
Nitrogen in soil	24 (Kg/acre)
Phosphorus in soil	30(Kg/acre)
Potassium in soil	40 (Kg/acre)

Then based on the given conditions, the crop suggested is “cotton” along with the amount of nutrients required for proper crop growth; the result is shown in figure 5.1.5.

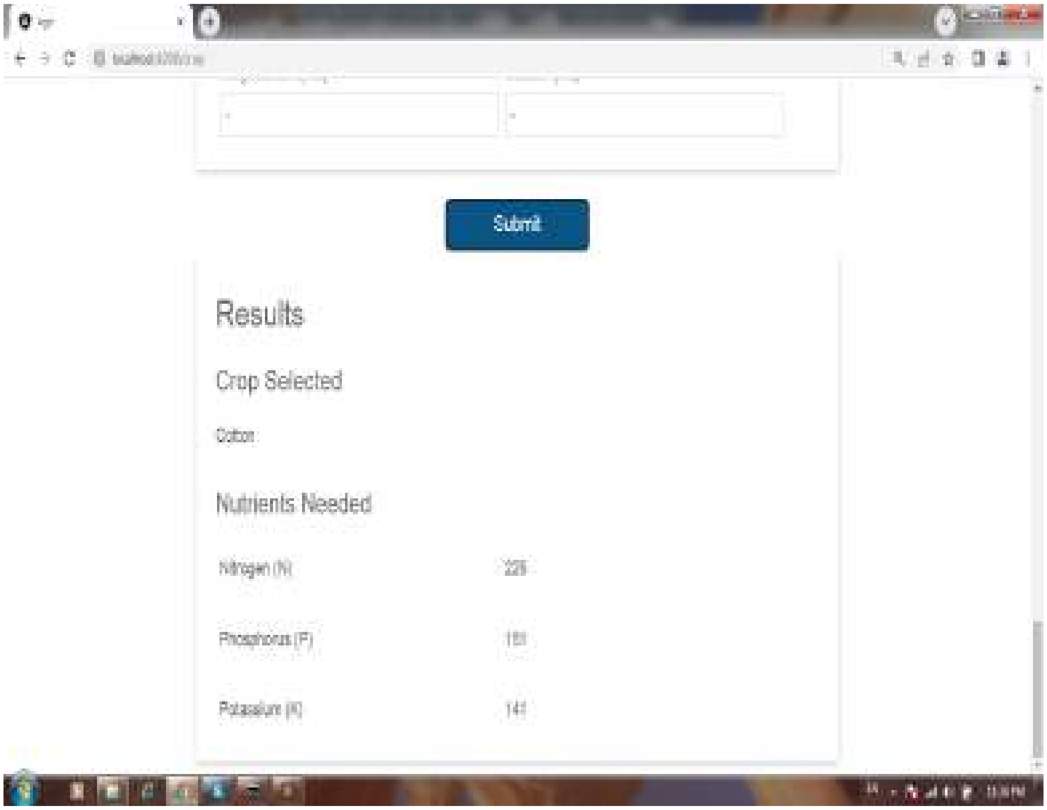

Figure 5.1.5: Crop Selection result

5.2 Ontology for IoT in Agriculture and Crop monitoring

The existing ontologies do not cover all the keywords and aspects needed for implementing semantic interoperability in IoT devices used in the agriculture sector. To ensure semantic interoperability in IoT devices used in agriculture, an Ontology has been developed, which provides a common knowledge base that can be shared by the IoT devices and Web interface to perform the tasks with semantic reasoning.

5.2.1 Graphical representation of the Developed Ontology

The Ontology has been developed using OWL_RDF; the developed ontology provides a conceptual representation of the IoT devices: Temperature sensor, Light sensor, Humidity sensor, Moisture sensor, and pH sensor. The graphical structure of the developed ontology can be visualized by using RDF graphs. Each node represents a Class, sub class entities and each edge represents relationship between those entities.

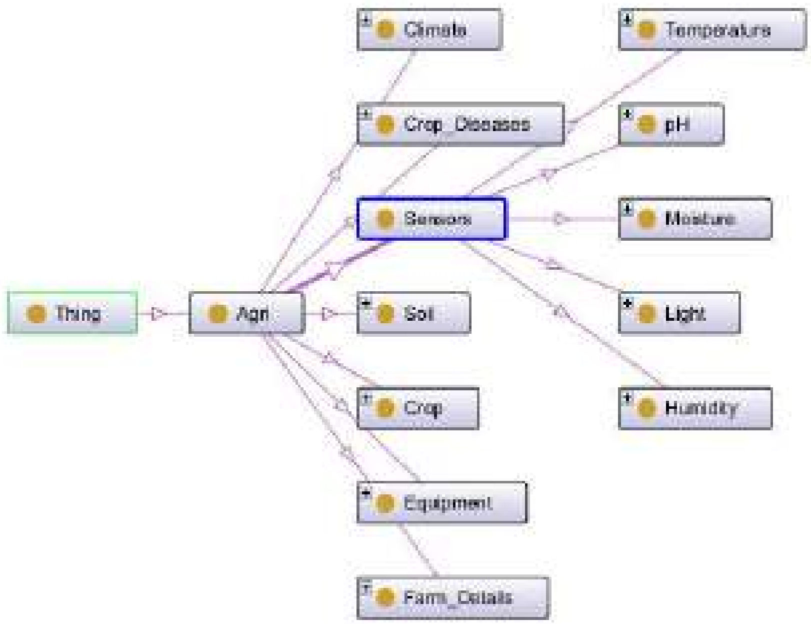

Figure 5.2.1.1: Sensors in the Developed Ontology

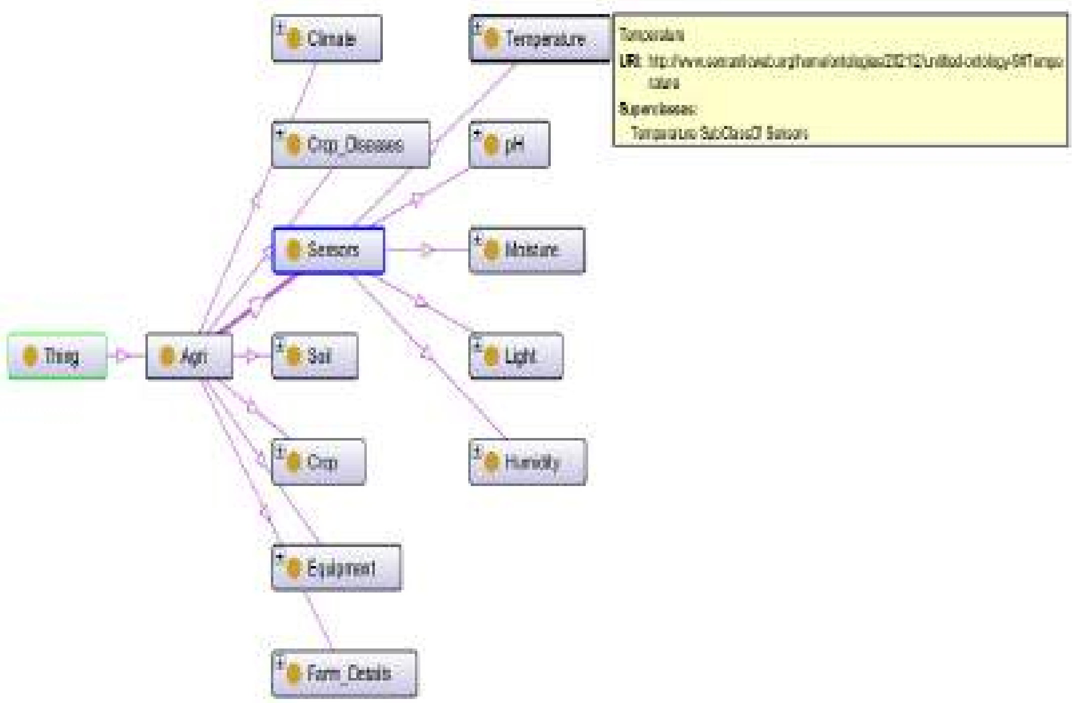

Figure 5.2.1.2: URIs

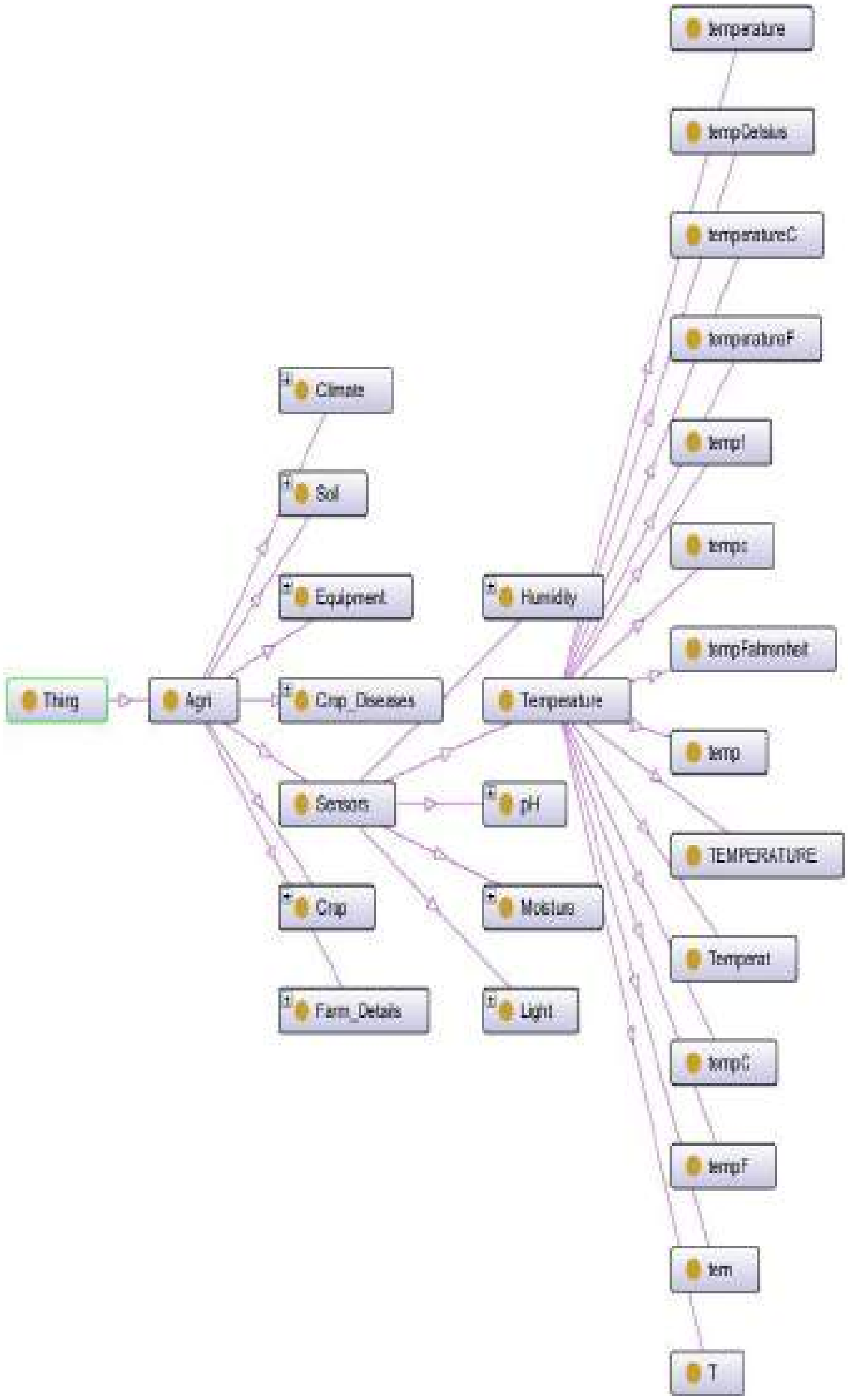

Figure 5.2.1.3: Knowledge graph for temperature sensor

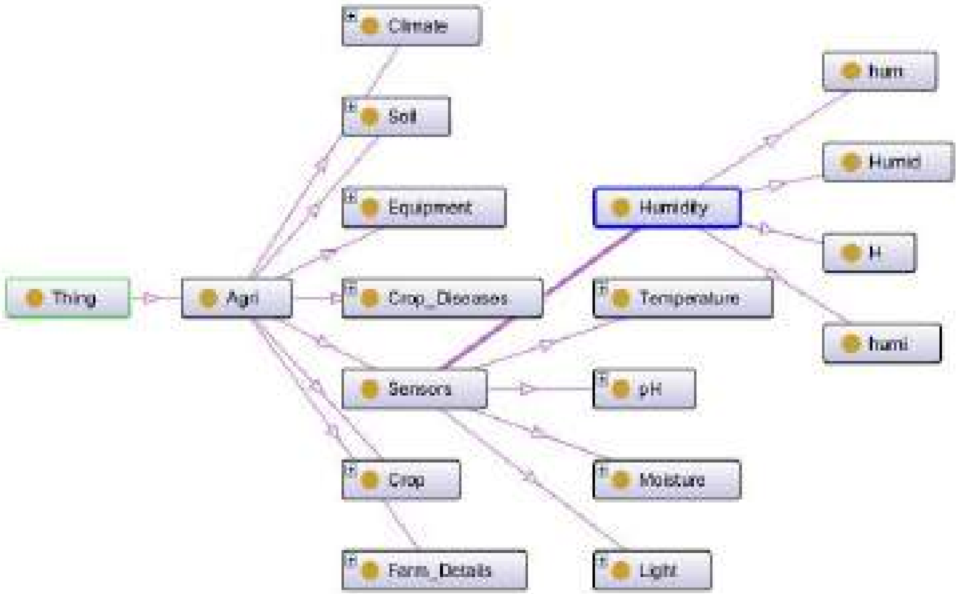

Figure 5.2.1.4: Knowledge graph for humidity sensor

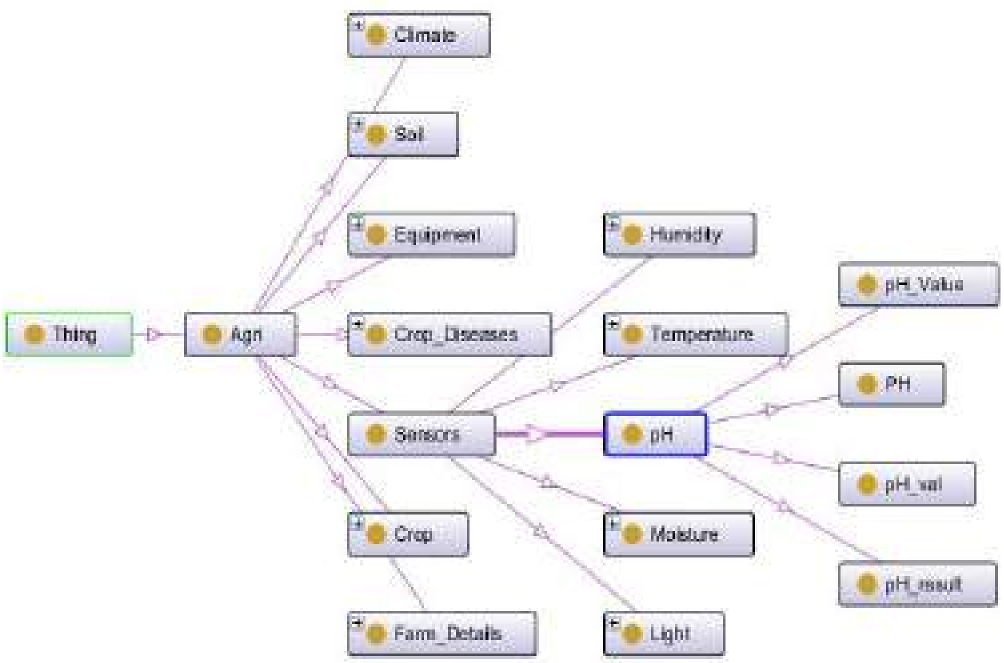

Figure 5.2.1.5: Knowledge graph for pH sensor

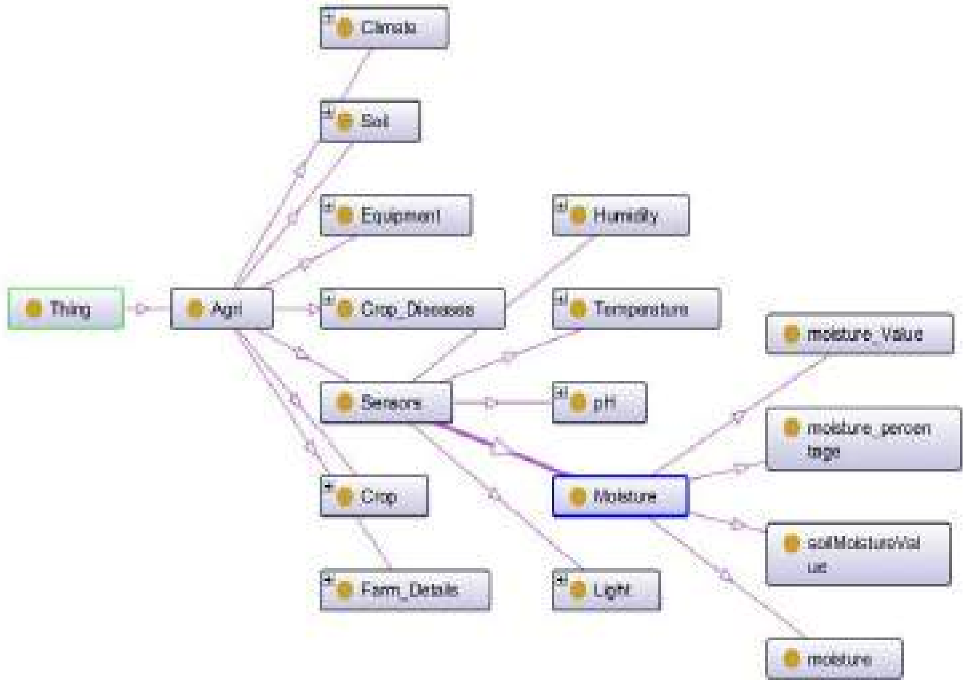

Figure 5.2.1.6: Knowledge graph for Moisture sensor

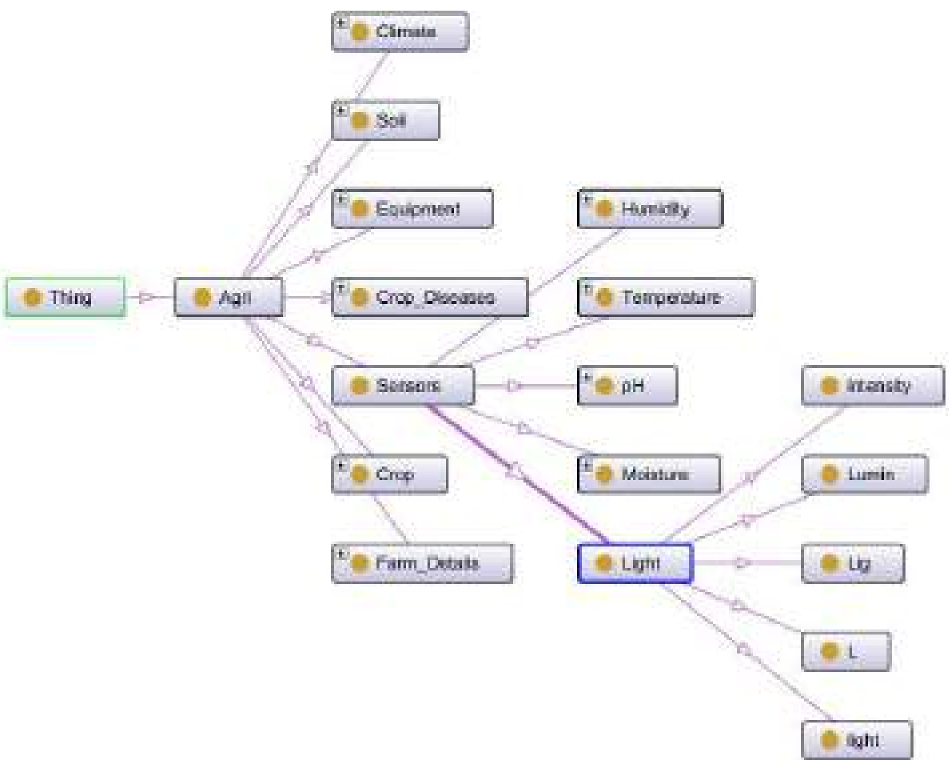

Figure 5.2.1.7: Knowledge graph for Light sensor

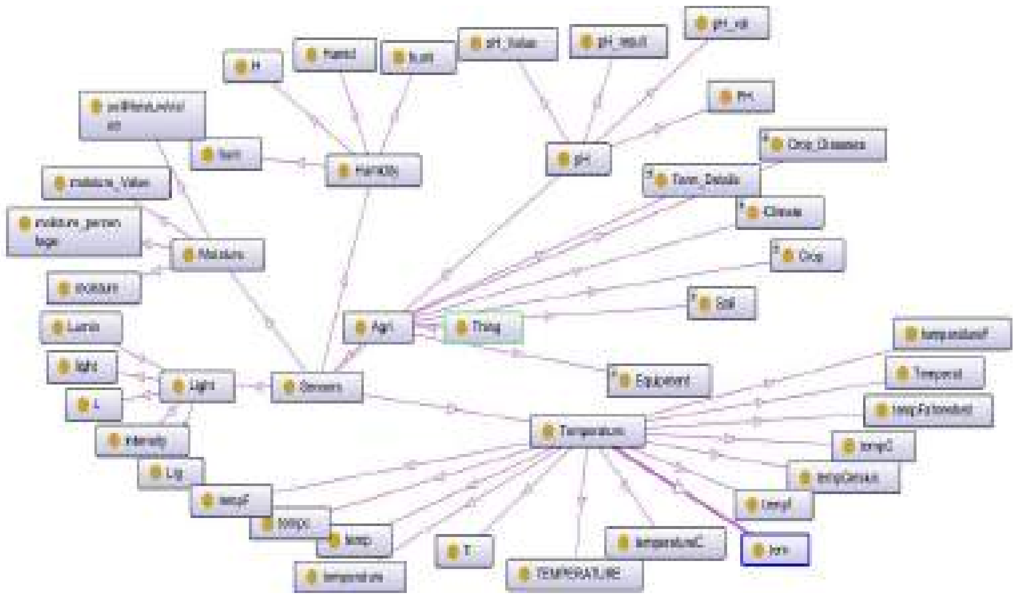

Figure 5.2.1.8: Ontology for IoT in Agriculture

As shown in the above figure, the developed ontology provides a semantic knowledge base for the IoT devices used in Agriculture, which enables the sharing of common vocabulary and Meta data across the IoT devices and web interface. The ontology functions as the brain for web applications and converts the data into a meaningful web of concepts. The developed Agriculture IoT ontology makes IoT software applications and IoT web interfaces work independently by sharing the common knowledge base.

5.2.2 IoT system setup in Cotton Field

For evaluating the performance of the developed frameworks, the live data is gathered by setting up the IoT system in Cotton Field. In a Field of one acre, one packet of Cotton seeds is sown in the month of June, and an IoT system with five sensors, Temperature, humidity, light, pH, and moisture, has been installed with the help of an Arduino board. The live data is gathered by using the online cloud service ThingSpeak. The conditions of the cotton crop are remotely monitored by using IoT generated data. The Agriculture IoT system can have devices from various manufacturers and system setups from different IoT service providers, which generates heterogeneous data; this data can be handled in a meaningful way by using the developed ontology. The data is parsed in the web interface by using the developed ontology.

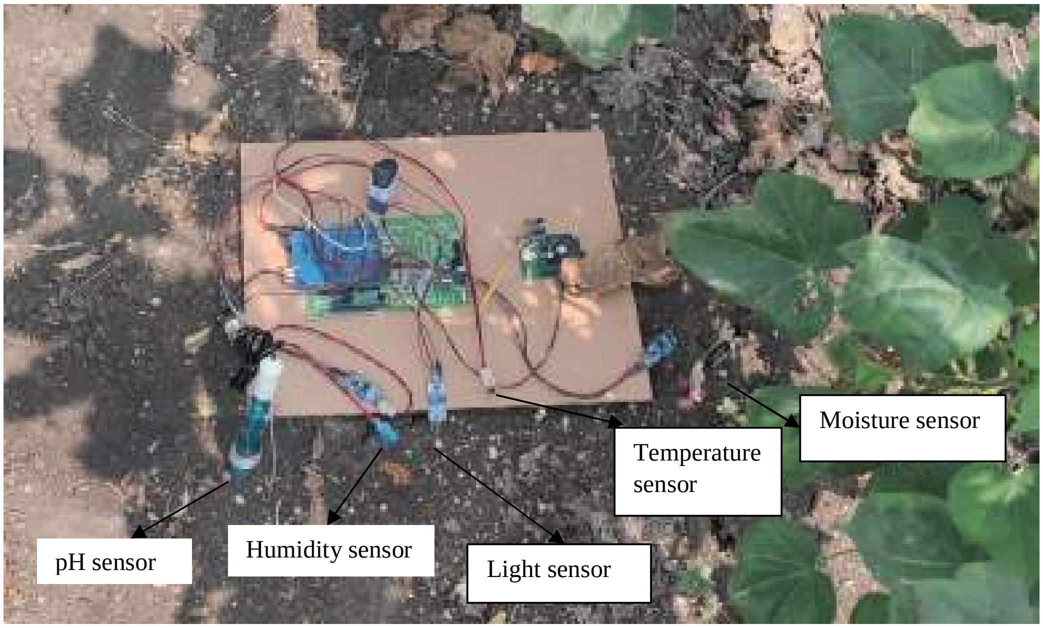

Figure 5.2.2.1: IoT system in Cotton Field

Figure 5.2.2.2: Monitoring cotton field

Figure 5.2.2.3: Live data collection

5.2.3 Data parsing and Ontology updation

The developed ontology is used to parse the meaningful data irrespective of tags with different aliasing names. If the ontology is not used, the garbage value is generated in the case of heterogeneous data.

When the user uploads the sensor data, the data is extracted properly if the keywords are present in the ontology. If the sensor keywords are missing from the ontology, the framework prompts which of the keywords are missing and the user can add them to the OWL file. The updated OWL file and JSON file can be downloaded for further use.

A sample of data generated from the sensors is parsed through the developed ontology. The keyword used for temperature sensor is *Temp*. The keyword used for the humidity sensor is *Hum*. The keyword used for light (intensity) sensor is *Light*. The keyword used for moisture sensor is *Moisture*. The keyword used for pH sensor is *pH*. As these keywords are present in the OWL file, the framework interpreted the data correctly and displayed the sensor readings. When the data is parsed without ontology, the values are not displayed.

The result of data parsing with and without ontology is shown in the following figure.

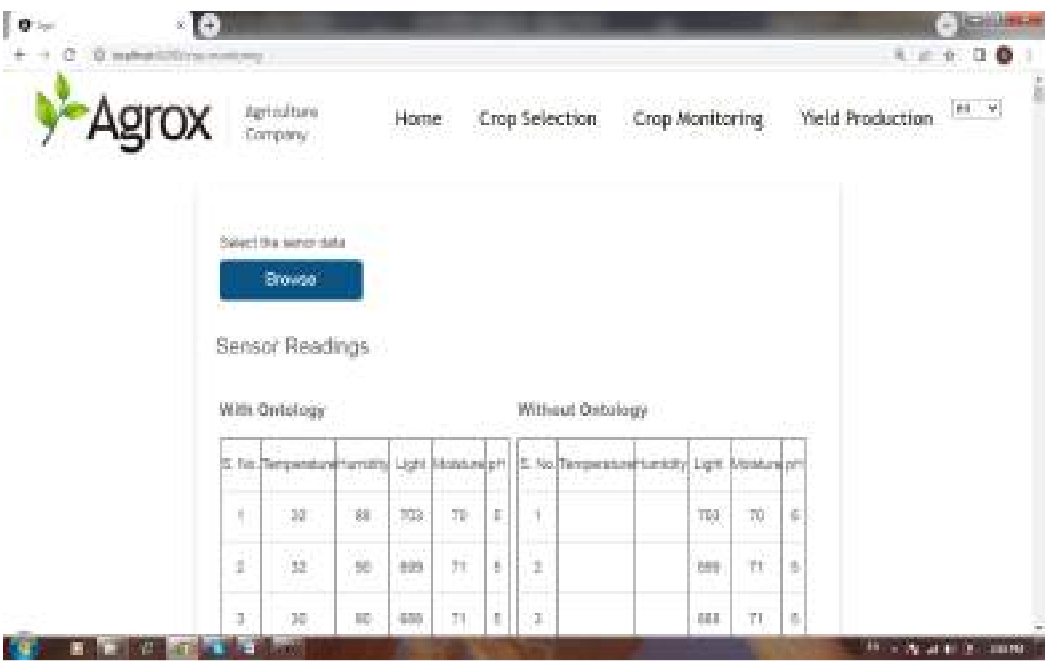

Figure 5.2.3.1: Data parsing

Ontology updation:

Whenever a new tag is encountered, the developed ontology is updated by adding the new tags and employing the ontology updation algorithm. For instance, if an input file of sensor generated data containing the new keyword for *Hum_val*, *Lt* is uploaded. The ontology parsing framework identifies that *Hum_val, Lt* is not present in the ontology. It asks the users to update the ontology, and specify the class and sub class in which the tag needs to be added, as shown in figure 5.2.3.2.

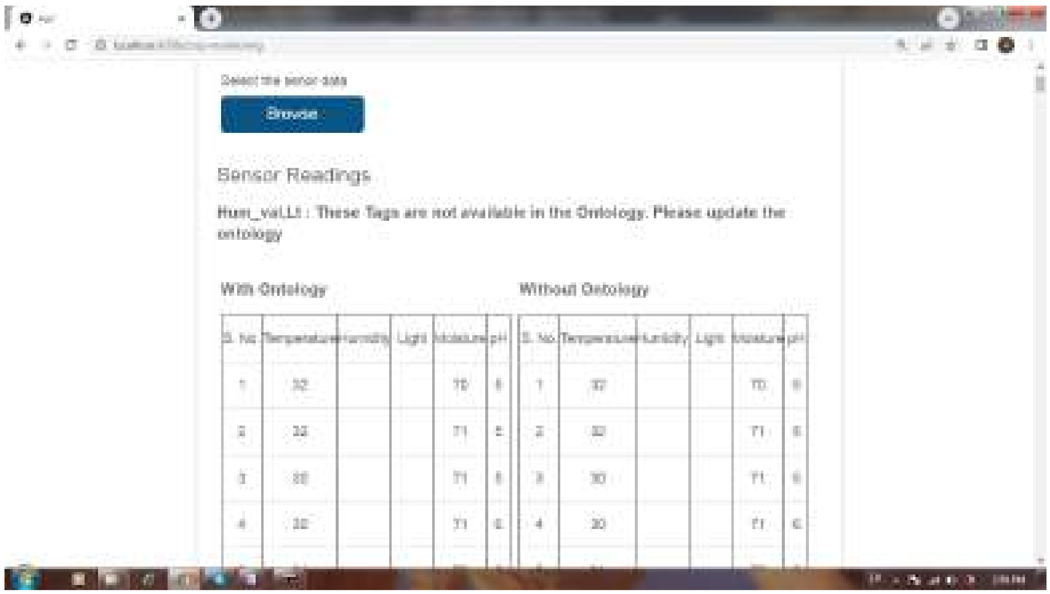

Figure 5.2.3.2: New tags for ontology updation

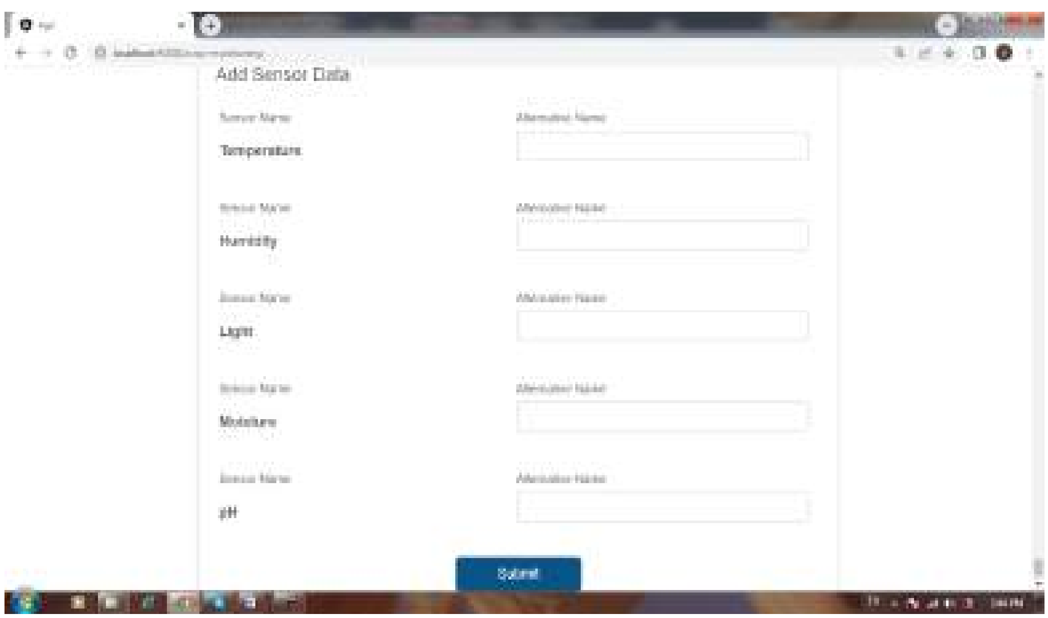

Figure 5.2.3.3: Adding new semantic tags in the ontology

Once the new keywords are submitted, a new ontology and a supporting JSON file are created. The tags of <*Declaration*> and <*SubClassOf*> are added to the existing ontology. The resultant output is shown in figure 5.2.3.4where all the sensor values are read as the ontology is updated.

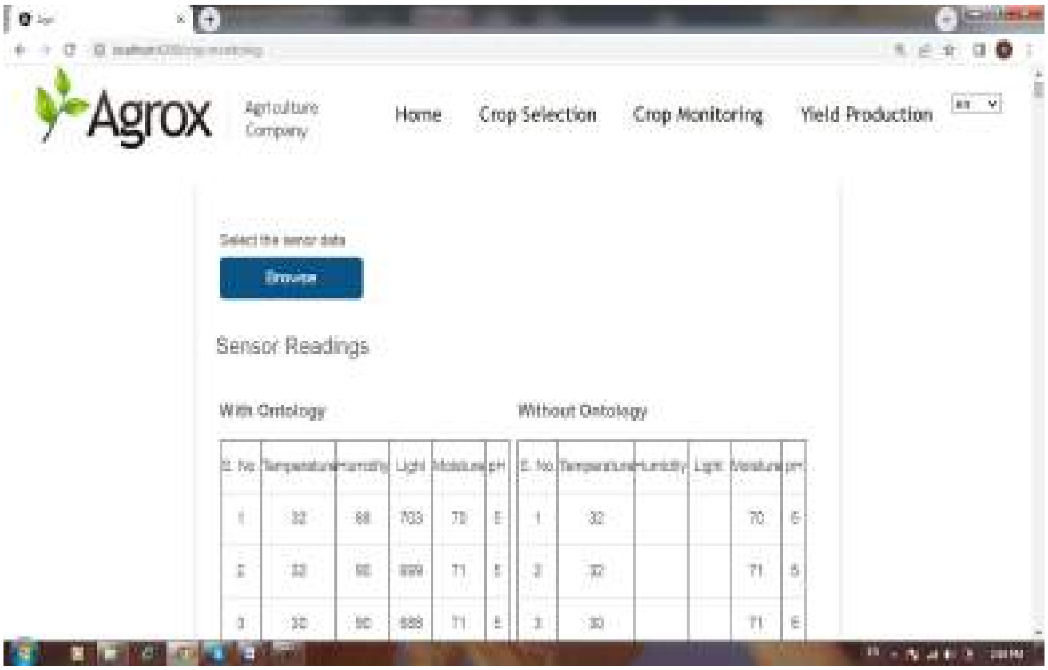

Figure 5.2.3.4: Data parsing using the updated ontology

5.3 Yield Prediction

As the cotton crop requirements change from time to time depending on the stages of growth, the weighted gradient linear regression model adapts different slope values for different stages for predicting the yield. The requirements of the cotton crop at different stages of crop growth are shown in table 5.3.1.

Table 5.3.1: Required Parameter Ranges for cotton crop

Months	**Temperature**	**Humidity**	**Light**	**Moisture**	**pH**
Jun to Sep	28-31 (°C)	68-74 (%)	700-800	70-80 (%)	4-7
Oct to Nov	30-32 (°C)	65-69 (%)	600-700	65-70 (%)	4-7

For the proper growth of cotton crops, the normal temperature range should be maintained in the early stages of growth, as it does not do well if the temperature falls below 21°C. During the last stage of cotton fruit development, warm days and cool nights are preferable.

The total cycle of cotton crop production is from June to November. As the IoT system has been used to monitor the cotton crop, the data generated from the sensors is used to analyze the crop conditions. The yield is predicted every two months, which helps the farmers in making more efforts for crop growth and also in planning the marketing of the crop. The final yield can be predicted more accurately based on the bi-monthly prediction data by applying the weighted gradient regression model. The bimonthly yield of the cotton crop is shown in table 5.3.2.

Table 5.3.2: Yield Prediction bi monthly

Month	Yield
Jun to Jul	14.25
Aug to Sep	14.06
Oct to Nov	13.49

The yield of June to July is 14.25, the yield of August to September is 14.06 and the yield of October to November is 13.49. The final yield prediction using Weighted Gradient Linear Regression is 13.94. The Actual final reported yield is 14.2quintals per acre.

5.4 Summary

In this chapter, the implementation details are presented, and the results of each phase are discussed in detail. The crop selection model is explained with practical input data. The developed ontology and its graphical representation are described in detail. The details of an IoT system setup in the Cotton field to gather real time data are provided. The results of yield prediction using a weighted gradient linear regression model are discussed.

Chapter 6

Results Discussion and Validation

6.1 Performance Evaluation

R-squared is a statistical measure used as a performance measure for the evaluation of the regression models; it indicates how well the developed model can fit the data. R^2 shows the proportion of variance in the dependent variable, which is defined by an independent variable; its value ranges from 0 to 1. The models with an R^2 value closer to 1 indicate the best fit.

MSE stands for Mean Squared Error; it is the average of the squared difference between model Predicted values and actually observed values. A small MSE indicates that the model is a good fit for the data, while a large MSE indicates that the model is a poor fit for the data.

RMSE stands for Root Mean Squared Error; It's the square root of mean squared differences between the model predicted values and actual values. RMSE is used to find more about size of the errors and helps in identifying the variability in data more accurately.

Table 6.1: Evaluation parameters of the proposed model

R^2	0.933328
MSE	0.066994
RMSE	0.258833

The proposed model obtained an R^2 of 0.933328, MSE of 0.066994 and RMSE of 0.258833.

6.2 Performance Comparison with Existing Yield Prediction Models

Linear regression is a statistical method used to model the relationship between a dependent variable and independent variables. The goal of linear regression is to find the line of best fit through the data points, which can be used to make predictions about future observations.

Nonlinear regression is a method used to model a relationship between a dependent variable and one or more independent variables that is not linear. Unlike linear regression, the relationship between the independent and dependent variables is not represented by a straight line. Instead, a nonlinear function is used to model the relationship, which can be more flexible and better able to capture the underlying structure of the data. Nonlinear regression can be used to model a wide range of relationships, such as exponential, polynomial, and logarithmic relationships. It is useful for modelling complex systems and for fitting data that does not conform to a linear model. The main disadvantage is that the results are not as easily interpretable as linear regression.

Exponential regression is a type of nonlinear regression in which an exponential function models the relationship between the independent variable x and the dependent variable y. An exponential function is a function of y = a*b^x, where a represents the initial value of y and b represents the growth rate. Exponential regression is often used to model data that shows a steady increase or decrease over time. It can be used to model phenomena such as population growth, radioactive materials decay, and disease spread. The main disadvantage of exponential regression is that it can only be used to model data that increases or decreases over time; it cannot be used to model data that oscillates or has a more complex pattern.

Table 6. 2:Comparative Analysis

	Linear Regression	Non Linear Regression	Exponential Regression	Weighted Gradient Linear Regression
R^2	0.912499	0.905573	0.912079	0.933328
MSE	0.238525	1.498352	0.172725	0.066994
RMSE	0.488390	1.224072	0.415603	0.258833

Weighted linear regression is a variation of linear regression in which the observations are assigned different weights. These weights are used to give more importance to certain observations and less importance to others when fitting the model. The weighting can be used to account for different levels of measurement error, to give more emphasis to certain subsets of the data, or to downweight outliers.

A gradient descent method is a optimization algorithm used to minimize a function, in this context the cost function of linear regression. The algorithm starts with an initial set of parameter values and iteratively moves towards a set of parameter values that minimize the cost function. The weights are used to adjust the step size and direction of the update of the parameters.

Weighted gradient linear regression is a combination of weighted linear regression and gradient descent. In this approach, the observations are assigned different weights, and the gradient descent algorithm is used to find the line of best fit that minimizes the cost function, taking into account the weights of the observations.

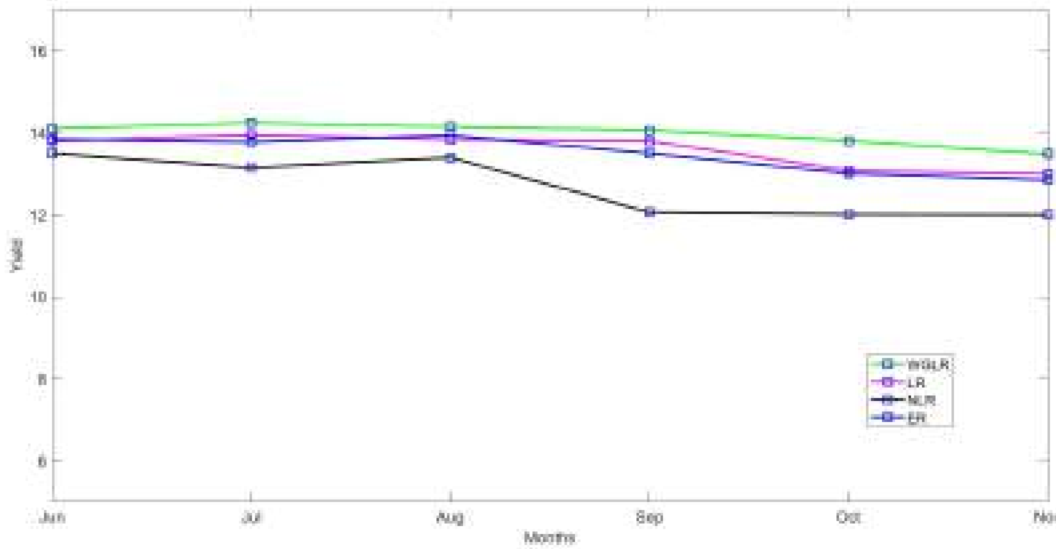

Figure 6.2.1: Yield prediction graph

The Figure shows the month wise yield prediction values obtained and a comparison of the results with other existing regression models. As the yield is predicted bi-monthly by applying the gradient, more accurate results can be obtained. As shown in the yield prediction graph, the predicted result of the developed model is close to the actual result.

6.3 Summary

In this chapter, performance measures for the evaluation of the developed yield prediction model are presented in detail. The R^2, MSE, and RMSE are estimated, indicating how well the developed Weighted Gradient Linear Regression model fits the data. Then, the final results are compared with the existing models, linear regression, non-linear regression, and exponential regression.

Chapter 7
Conclusion and Future Scope

7.1 Conclusion

IoT No matter the manufacturer or protocol, devices and systems must be able to operate together effortlessly and communicate effectively. This is known as semantic interoperability. In agriculture, IoT Semantic interoperability can help improve efficiency, productivity, and crop yields by allowing farmers to collect and analyze data from a variety of sources, such as weather sensors, soil moisture sensors, and drones. This data can be used to optimize irrigation systems, predict crop yields, and identify areas of the farm that need attention. Additionally, IoT interoperability can also help in reducing costs by allowing farmers to use off-the-shelf devices and systems rather than proprietary ones that can be more expensive and difficult to maintain. Overall, IoT Semantic interoperability can help farmers make more informed decisions and ultimately improve their agricultural operations.

A group of technologies known as the Semantic Web intends to improve the machine understanding of content on the World Wide Web. The usage of ontologies, that are formal definitions of the ideas and connections in a specific domain, is one of the core components of the Semantic Web. In agriculture, ontologies can be used to represent information about crops, soil types, weather patterns, and other relevant factors. This allows data from different sources to be linked and integrated, making it more useful for analysis and decision-making.

Another key feature of the Semantic Web is the use of RDF (Resource Description Framework) and linked data, which allow data to be linked and shared across different systems. This allows farmers to access and use data from a wide range of sources, such as government agencies, research institutions, and other farmers, which can help them make more informed decisions and improve their agricultural operations. Overall, the Semantic Web can help farmers access and make sense of a wealth of data, and make better-informed decisions to improve their agricultural operations and ensures semantic interoperability in IoT devices used in Agriculture.

Ontologies play a major role in bridging the gap between the database and the sensor data. When processing the search, ontological derivation knowledge, and ontological definitions, serves to bridge possible inconsistencies in the formulation of the search and the available information. Furthermore, a similarity-based search is made possible by using background knowledge. This research work presents the development of dynamic agriculture ontology along with the ontology framework that can extract the informative metadata from any existing ontologies OWL files. Ontology updating algorithms are developed, which provide means of updating the OWL file and the JSON file at the same time. A new OWL file and JSON file are produced at the output, which can be easily parsed by many platforms. The developed ontology helps in parsing the sensor data files accurately without missing any information.

To forecast agricultural yields, machine learning systems examine historical data, including weather patterns, moisture levels, as well as other environmental parameters. This enables farmers to choose planting, irrigation, and fertilising strategies with more knowledge. Machine learning models may be taught to recognise trends in sensor data that point to an issue, like illness or pests, in a particular region of the farm. This can help farmers quickly respond to potential issues and minimize crop loss. Machine learning models can also be used to optimize the use of resources, such as water and fertilizer, by identifying the areas of the farm where they will have the most impact. This can help farmers reduce costs and improve crop yields. In this research work, a crop yield prediction system is presented that makes use of a Weighted Gradient Linear Regression model to make the yield predictions. In order to provide an accurate prediction of the yield, the prediction model takes into account a number of different characteristics, including temperature, humidity, light, moisture, and pH. The yield prediction model estimates the yield based on a gradient of the attributes of each component, which is determined by dividing the input data into separate parts. The Weighted model is used to assign relative importance to the various parameters in relation to the stage of the crop.

7.2 Future Scope

The Internet of Things (IoT) and the semantic web have the potential to revolutionize agriculture by enabling more efficient and precise farming practices. Interoperability, the ability for different devices and systems to communicate and work together, is crucial for the successful implementation of IoT in agriculture. The semantic web, which involves the use of standardized data formats and ontologies, can improve the ability of IoT devices to share and interpret data. Together, these technologies can enable farmers to monitor and control various aspects of their operations more effectively, such as crop growth and soil conditions, leading to improved yields and reduced costs. In the future, these technologies will continue to evolve and be integrated into more aspects of the agricultural industry.

IoT sensors can be used to monitor a wide range of agricultural conditions, such as soil moisture, temperature, and nutrient levels. This information generated from the IoT sensors can be used in crop selection, disease predictions, weed-controlling systems, automatic irrigation systems, fertilization, and other systems supporting critical aspects of farming operations. In the future, IoT sensors will become even more advanced and sophisticated, with the ability to collect and analyze more data and make more accurate predictions. As the technology keeps on evolving, in the future, there is a possibility that the new equipment and new technologies will collaborate with the IoT devices to develop more advanced applications; the ontologies need to be upgraded by adding the terms, concepts, and relations related to new sensor devices and equipment to support these kinds of advanced applications. Precision agriculture, which uses IoT sensors and other technologies to optimize crop growth on a field-by-field basis, will become more prevalent. This will allow farmers to make more informed decisions and reduce waste.

IoT-enabled Smart Agriculture systems, along with the semantic web technology, will be more prevalent in the future; these systems can be used to monitor, control and automate various agricultural processes such as irrigation, fertilization, crop growth, and livestock monitoring effectively with semantic reasoning. The use of drones and autonomous vehicles equipped with IoT sensors will also become more common, allowing for more efficient and cost-effective monitoring and management of large areas of land. The use of IoT with blockchain technology in agriculture will allow the secure and transparent tracking of food from the farm to the consumer, which is important for ensuring food safety and for meeting the traceability requirements of the industry. In addition, due to the advancement in technologies, the IoT has started combining with other technologies such as big data, machine learning, semantic web, blockchain, etc., which provides a huge scope of further research for developing more advanced applications for the agriculture sector.

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Appendix A

List of Publications

Published papers:

1. Khatoon, PS, Ahmed, M. (2022) Importance of semantic interoperability in smart agriculture systems. *Transactions on Emerging Telecommunications Technologies, (Wiley publications),*Volume 33, Issue 5:e4448. https://doi.org/10.1002/ett.4448 (An SCIE (Science Citation Index Expanded)indexed journal)**.**
2. Khatoon, P.S., Ahmed, M. (2021). Semantic Interoperability for IoT Agriculture Framework with Heterogeneous Devices. In: Gunjan, V.K., Zurada, J.M. (eds) *Proceedings of International Conference on Recent Trends in Machine Learning, IoT, Smart Cities and Applications. Advances in Intelligent Systems and Computing*, vol 1245. Springer, Singapore. https://doi.org/10.1007/978-981-15-7234-0_34. (Scopus-indexed Springer conference proceedings)
3. Khatoon, P. S. and Ahmed, M.(2021). A Crop Selection Framework using K Nearest Neighbour for IoT Semantic Interoperability Applications, *2021 8th International Conference on Computing for Sustainable Global Development (INDIACom)*, pp. 262-267. (IEEE conference Proceedings)

Communicated Papers:

1. "Design and development of dynamic Agri-Ontology for IoT Interoperability", in International journal of communication systems, Wiley publications (Science Citation Index Expanded (**SCIE**) indexed).

Conference Presentations:

1. "Semantic Interoperability for IoT Agriculture Framework with Heterogeneous Devices" at International Conference on Recent Trends in Machine Learning, IoT, Smart Cities and Applications From 28th-29th March 2020 organised by CMR Institute of Technology, Hyderabad.

2. “A Crop Selection Framework using K Nearest Neighbour for IoT Semantic Interoperability applications” at 2021 8th International Conference on “Computing for Sustainable Global Development”, 17th-19th March, 2021, BVICAM, New Delhi (INDIA), IEEE Conference ID: 51348.
3. “A Dynamic Ontology Framework Design to Provide Interoperability in Agriculture IoT” at Two-Day National Conference on Computational Methods, Data Science and Applications (NC-CMDSA 2021) held on 24th-25th May 2021, organized by MANUU, Department of CS&IT, Hyderabad.

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Degree (M. Phil / Ph. D.)	Ph.D.
Department / Centre / Institution	Computer Science & Information Technology
Guide/Supervisor	Dr. Maqeem Ahmed
Thesis / Dissertation Title approved in DRC held on :	Title: Development of an Effective Semantic knowledge Base for IoT in Agriculture Date: 27/05/2022
Registration Date	24.07.2018
Submission Date	24/01/2023
Key words	IoT, Semantic Web, Agricultural Ontology, Machine Learning, Yield Prediction
Language of Thesis	BILINGUAL
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