JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

STUDY ON AUTOMATIC AGRICULTURE PREDICTION USING IoT AND DEEP LEARNING

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***Abstract*:** The main and largest manufacturing sector throughout the world was agriculture, which has evolved from the prehistoric age to the technologically advanced 21st century, where individuals are constantly using gadgets to solve complicated challenges. The Internet of Things (IoT) connects every digital object in existence, making the globe a global community thanks to the power of Information and Communication Technologies (ICTs). Almost every business, including farming, has experienced radical change as a result of the rapid spread of IoT-based technology, which has replaced statistical with quantitative methods. Such deep changes are changing conventional farming methods and opening up new opportunities in the face of diverse difficulties. Farmers may now track the state of their crops in actual time because of the changes that have been provided. Farmers can automate tasks in the farmland with the help of automated IoT solutions because these solutions are capable of making accurate decisions based on underlying challenges or performing actions to overcome such challenges, alerting farmers in real-time, and ultimately resulting in increased productivity and largest harvest. In this context, they demonstrate the need for smart farming by introducing a cloud-enabled low-cost sensorized system for real-time monitoring and managing chores on a tomato plantation in an indoor environment. The results of this research are expected to be crucial in creating and marketing smart farming solutions that will improve quality and output while also facilitating the shift to sustainability ecology.

Index Terms: Internet of Things; Agriculture; Cloud System; Deep Learning; Information and Communication Technology

I. INTRODUCTION

India is known as an agricultural country. More than 65% of primary and secondary business is based on farming. With a growing population, crop production needs to be increased [1, 2]. The pH range7.5 to 6.5 is considered neutral. Numerous soil elements that affect plant growth, including nutrient leaching and soil micro-organisms are influenced by soil pH [3]. Technology has shown continuous improvement in the farming industry by continually updating and requesting new technology to make farming easier. Predictive modeling is crucial for optimal farming methods to improve farm profitability [4]. ML approaches have been used on the dataset collected from IoT devices to predict crop yield production, and intelligent tools are developed with the help of ML models [5]. Remote sensing presents useful insights into the agricultural ecosystem for determining sustainable and optimal solutions [6, 7]. Modern research focuses mainly on crop productivity and sustainability challenges [8], which include crop analysis and obtaining optimal results using neural network models which can work with large data, and loss of data does not reduce the performance of the model. The recent findings show that the study focuses more on promoting soil performance and the use of DL and IoT technology in digital agriculture to enhance the performance of existing technologies and increase the productivity per unit of land [9], enhancing agricultural productivity using neural network models and computer vision techniques, sustaining the environment and future agriculture productivity by advancing integrated technologies [10-12].

The information obtained from farmland is available in dataset which can be used to make well informed decisions [13]. The ML and DL models accurately train the dataset to predict what combinations of the environmental conditions and yield data can increase production rate [14, 15]. In farming, the required resource inputs for crops are water, fertilizer, pesticides which are supplied uniformly throughout the field, ignoring the natural inherent and heterogeneous nature of soil and crop conditions [16]. This uniform spread of resources will lead to either over or under-application of resources which is harmful to crop growth. Fertilizers should be recommended based on the type of crop, soil type, and pH of soil [17].Rainfall also plays an important role in increased crop production [18].

Early disease detection and classification is possible using modern agriculture technologies such as deep learning techniques [19]. Farmers will face huge economic losses when prices of agricultural products fall after the harvesting and the GDP of the country will be affected due to price fluctuation in agricultural products. Prediction of price will help farmers to minimize loss and manage risk due to price fluctuation [20]. It has been reported that 10% to 15% of US farmers use IoT solutions in farming across millions of hectares, and results showed improved production [21].

The study focuses on commodity price prediction based on history of the market prices of various commodities collected from various APMC's of Karnataka. The ARIMA and LSTM model is used for forecasting market prices of commodity for the Karnataka region [22]. The automated irrigation system needs to be employed in the agriculture sector to optimize irrigation management [23].

The proposed workflow of the research is shown in Figure 1 the study uses a dataset that includes both environmental data and yield data. Environmental data includes Rainfall, NPK, Soil pH, soil type, season and Yield data includes historical crop yield, and area of production [24]. The dataset is preprocessed and normalized to the required form and for efficient prediction ML algorithms are used such as LSTM, Genetic Algorithm based Evolutionary Algorithm (EA), Convolution Neural Network (CNN), ARIMA, Back Propagation (BP) model, and Linear Regression (LR) for accurate prediction of crop yield, plant disease detection and classification, commodity price prediction, and LR is applied on real-time data for analysis which is collected using IoT technology. The performance of these algorithms is measured using metric RMSE and MAE, the lowest metric values are recorded and compared with conventional algorithms [25]. Recorded parameters are used for prediction and finally, optimal results are obtained. It is a grouping of real things that are linked together physically [26]. Humans, animals, transportation, environments, and appliances are examples of physical things. However, the term "Internet" denotes the notion that "Things" are interconnected to it, and a unique identifier identifies each "Thing" [27].

The IoT's qualities and capabilities, in general, allow it to be utilized in various applications [28]. As defined by [29], Precision agriculture utilizes Information Technology (IT) to enhance crop quality and boost production. In 2050, the world's population is estimated to increase by 36% to 9.6 billion people. In the next 30 years, food consumption might significantly rise to 3070 kcal/person/day [30]. The atmospheric dampness, sensors monitor temperature, soil moisture levels, and other factors like water content, outside temperature, air velocity, etc [32]. According to [32], PA is considered a data-driven strategy. Researchers employ data mining techniques (classification, clustering, regression, and so on) to address a complicated topic and provide predictions.

II. IoT AND ENABLING TECHNOLOGIES IN SMART AGRICULTURE

Numerous technologies are included in IoT agriculture solutions. It's difficult to express all of those explicitly. Our discussion centered on a fewcritical technologies that have been instrumental in upgrading IoT agriculture services.

Wireless Sensor Network (WSN)

A WSN uses multiple fixed and mobile devices that have sensors to measure various physical and environmental parameters. Wireless sensor networks comprise routers, nodes, and coordinators [33].

Cloud Computing

Through the internet, it enables the use of apps as services. Anything present in far-off places is referred to as a "cloud." Users may access any number of resources, such as web servers, databases, and memory/storage, through the web using cloud computing.

Deep learning

The (ANNs) are used in the ML technique known as deep structured learning to learn patterns. Unsupervised, supervised learning and semi-supervised, were the three forms of learning [34].

The most general shallow framework includes Support Vector Machines (SVM), Gaussian Mixture Models, and Logistic Regression [35].

III. RECENT INNOVATIONS INVOLVED IN THEAGRICULTURE FIELD

Using deep learning approaches, [36] analyzed 40 research projects addressing a variety of agricultural and food production issues. Analysis of the specific models used, data sources and performance, the hardware used, and real-time application possibilities to explore potential integration with autonomous robotic platforms are discussed by [37]. A large increase in food production is necessary to meet the increasing demand for food, while also maintaining global accessibility, good nutritional quality, and ecosystem protection through the application of sustainable agriculture practices [38, 39]. The primary of this study was to develop how agriculture and food production may benefit from deeper learning. Compared the effectiveness of DL in farming with that of other artificial intelligence models already in use in agriculture [40].

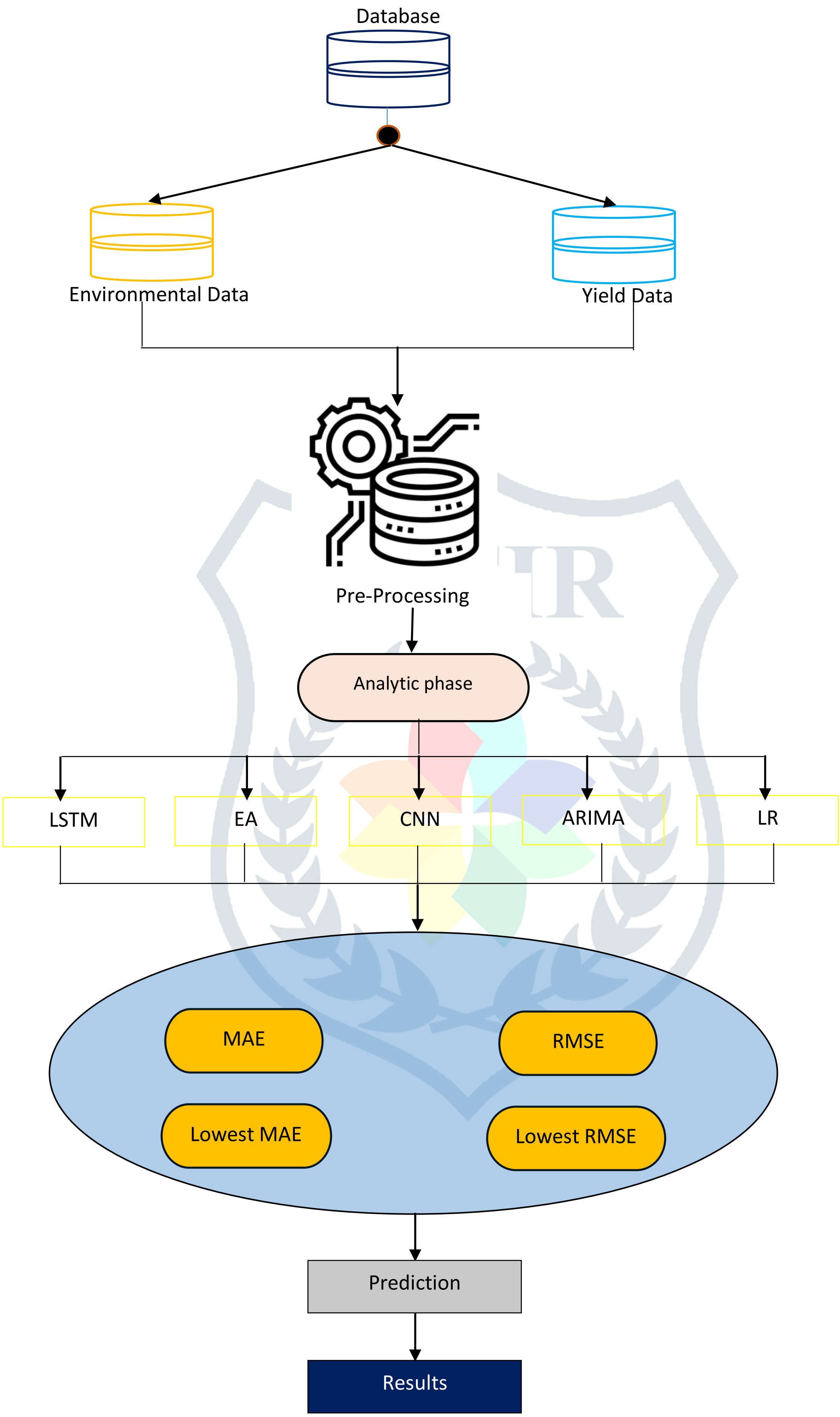

Figure 1: Workflow of the Proposed Model

3.1 Neural Networks

For the collection of soil data, [41] employed a near-infrared reflection sensor, which they then analyzed using multiple linear regressions. It was also shown that the Time Domain Reflectometry (TDR) device can accurately estimate soil moisture by using a grey correlation model developed by [42]. To manage planting in different areas, the model must be constructed with more efficiency, even though empirical derivations are straightforward. [43] Developed yet another soil moisture regression model using linear regression. It was built using Artificial Neural Networks to forecast soil quality utilizing meteorological variables and real-time data, as reported by [44, 45]. Unsupervised learning does not require a known output to match the training set's input patterns [46]. This section discusses a few more articles on design techniques used in existing research in agriculture applications using ML, DL, and IoT technology for predicting crop yield, plant disease classification, and agro-product price prediction, and real-time environment monitoring and the analysis of these articles is shown in Table 1.

Table 1: Analysis of Recent Papers in the Field of Agriculture

References	Design Technique/Methodology	Analysis
[1]	The design technique uses two neural networks and training is performed on both, one for the yield and the other for check yield, and differences in their outputs are used as prediction.	The model learns the non-linear and complex relationship between environmental conditions, genes, and their interactions from previous (historical) data using which it makes accurate predictions. The RMSE value obtained is 12% for the average yield on the training dataset. The results show that environmental features have a greater effect on crop yield. The DNN outperformed the other three algorithms i.e., Spiking Neural Network, Regression Tree, and Lasso. The model is more effective then using a single neural network
[2]	This paper employs Bayesian Hyperparameter Optimization (BHO) for optimization and aggregating bootstrap to improve the performance of the model.	Corn yield data were taken from the year 1979 to 2016. While training, the authors converted nonparametric covariants into a matrix of principal components. The proposed model reduces the L2 regularization loss value through gradient descent by back propagation.
[3]	Fifty papers are surveyed in this review paper. In all papers, ML models are used to predict crop yield. Research questions are defined and the database is used to select the most relevant studies.	Important features for crop yield prediction are rainfall, soil type, and temperature. ANN was the more applied technique and the study also shows most extensively used algorithms are the DL method, CNN, and DNN, and among these LSTM is the most preferred algorithm. DL is the sub-branch of ML which created state of art outcomes with accurate prediction.
[4]	The CNN-based approach is applied which consists of a design technique with 3 layers of convolution, 3 max pool layers, and 2 layers fully connected and the dataset consists of 9 disease classes with one healthy class. The dataset is not balanced so, augmentation is applied to balance the dataset.	Tomato leaf disease classification is made using the CNN model and pre-trained VGG16, Inception V3, and MobileNet. The Results showed an accuracy of 77.2% for VGG16 model and Inception V3 at 63.4% and MobileNet at 63.75%. Therefore VGG16 showed better accuracy when compared to other models. The study showed a CNN model with an accuracy of 91% that is considered better than pre-trained models.
[5]	The automatic coffee disease detection model is built using texture attribute detection techniques for pattern recognition and input texture attribute vector to the CNN model.	This study applies computation methods to detect diseases in coffee leaves. The two texture attributes considered are statistical attributes and local binary patterns. The experimental results showed the best kappa coefficient of 0.97 and sensitivity with 0.98. The results show both methods are suitable for disease detection.
[6]	ML models are applied for the prediction of commodity prices. The wavelet analysis method is used in this study for data smoothing and ARIMA is applied for forecasting.	Various technical indicators have been applied for future price prediction like moving average, exponential smoothing moving average, relative strength index, and stochastic. This study forecasts the price trend. The prediction model used for this study is a support vector machine to optimize the price of a crop.

[7]	Precision irrigation technology is used that involves cloud computing, WSN and IoT. A real-time smart irrigation model is built and sensors are deployed in the field and sensed data is transmitted through MQTT communication protocol to the gateway.	Water requirements for crops vary with weather conditions and type of crop. The smart irrigation system is designed using IoT technology which senses real-time data and water is supplied based on necessity by saving water consumption and reducing manpower and money. The data sensed is sent to the central node i.e., Raspberry Pi. Automatic water management takes place when the moisture level is less than expected and the user is intimated using mobile application.
[8]	This paper discusses the design and development of an automatic Decision Support System (DSS) for irrigation management. The model is trained with a dataset that consists of soil and climate data.	This model proposed DSS for irrigation management. Different sensors are created in the field to manage the irrigation system. The obtained data is stored in the server for analysis. The proposed model uses regression-based algorithms to train and build the irrigation DSS using a support vector machine, random forest, and linear regression. Random forest shows improved results compared to other models.
[9]	This paper aims to design a deep CNN-based pre-trained VGG16 model for the classification of paddy crop disease. The methodology includes two stages i.e., data preparation and classification.	CNN-based VGG16 classification model is used to detect 12 categories of paddy crop disease which showed the accuracy of 92.89%. Two categories of crop stresses are detected i.e., leaf injury and color variation by visual scoring symptoms learning over 6000 images.

3.2 Classification Methodologies

A technique for detecting illnesses in citrus trees using machine vision was developed by [47]. Researchers [48] used rice leaf analysis to identify mineral deficits and illness. When plants are deficient in minerals, it shows up as brown spots and blast illnesses, which cause different-sized and shaped lesions on the leaves of the plants.

This conducted research to illustrate how a data group model and a data fusion model enhance prediction [49]. They compared variable-rate K-means clustering with their previous results. In a study by [50] nutritional deficit in palm trees was discovered. First, pictures are segmented by color similarity and then processed as a single image using their approach. Discovered that utilized image processing and a classifier to find illnesses in blood samples[51]. Plant village is a large dataset that has been used to train and test several deep-learning models, including DigiPathos [52].

According to [53], RSC characteristics are extracted from plant leaf pictures using an SVM classifier, and the system is used to identify and classify plant leaves automatically. This used the (GLCM) and PCA techniques to extract leaf texture characteristics [54]. The Algorithms are trained on 390 leaves to identify 13 different species of plants, each having 65 fresh or deformed leaves as test pictures.

3.3 Soil Quality Assessment

Investigated different destinations to foster an exhaustive technique for surveying soil quality [55]. When it comes to traditional ways of assessing soil fertility, there are three to choose from: the fuzzy comprehensive evaluation method, the grey correlation analysis method, and the analytic hierarchy process [56,57]. Thus studied the methods that are computerized picture-handling systems to detect measure and arrange plant illnesses from advanced images in the unmistakable range [58]. Even though illness side effects might show in any section of the plant, solely approaches that study apparent side effects in leaves and stems were evaluated. To help farmers make more informed decisions regarding many aspects of the harvest-creation process, suggested a study they conducted.

IV. IOT DEVICES AND SENSORS IN AGRICULTURE

A sensor is an electronic device that can meet people's needs by recognizing and responding to the same input from the physical world. Users can program sensing devices to execute tasks without the need for human intervention. The widely used IoT sensors include Soil Moisture, Motion Detectors, Temperature, Barometric Pressure, Humidity, pH, Ultra Violet(UV), Passive infrared (PIR), and gas sensor. This section covers a variety of agricultural sensors, along with their functions and IoT connections,

- **pH Sensor**: A pH sensor keeps track of the precise ratio of soil nutrients that are required for irrigation. The appropriate amount of nutrients is provided to the crops or plants for healthy development by checking the pH value.
- **Gas Sensor:** Gas sensors assess the amount of hazardous gases in greenhouses by tracking the number of infrared radiations absorbed. It is made up of two components: low range and high range; the former starts at 0 and goes up to 10,000, whereas the latter begins at 0 and goes up to 100,000.
- **Ultra Violet (UV) Sensor:** These sensors convert photons to electric current and detect ultraviolet radiation. It includes an external source that converts an analog signal into digital signals.
- **Motion Detector Sensor:** These sensors are beneficial at night, primarily for detecting wildlife and robbery in the outdoors. By sensing the direction of an undesirable object or creature throughout the farm, the farmer may take remedial measures.
- **Passive Infrared Sensors:** To sense the environment, a motion sensor is installed in the Passive Infrared (PIR) Sensor, which

is used to verify an individual's movement range.

❖ **Soil Moisture Sensor:** The moisture content and amount of water in the soil are measured using this sensor. It is made up of two big exposed pads that operate on the principle of electrical conductivity.

❖ Temperature Sensor: The temperature of the soil has a significant impact on crop productivity. Soil's moisture content and absorption of nutrients are directly affected by changes in soil temperature.

❖ **Humidity Sensor:** This sensor detects and monitors the relative humidity concentration in the atmosphere. It determines the temperature and moisture level in the air.

❖ **Barometric Pressure Sensor:** These sensors detect air pressure and control water flow; when pressure is low, rainfall is anticipated; when it is high, rainfall is uncertain.

V. SUITABLE SOIL FOR AGRICULTURE IN TAMILNADU

Soil is the key factor in agriculture to increase the productivity of the crop. The quality of the soil plays a vital role in growth of the plants and crops. In Tamilnadu, there are different types of soil in different agro-climatic zones. Table 2 and Figure 2 gives the district-wise details of different types of soil in Tamilnadu and are taken from the Tamilnadu agricultural university data.

Table 2: Different Soil Types for Agriculture in Tamil Nadu

Zone	Districts	Soil type
North EasternZone	Vellore, Tirunvannamalai Villupuram, Tiruvallur, Cuddalore, and Kancheepuram	Clay Loam,Red Sandy Loam, Saline Coastal Alluvium
North Western Zone	Dharmapuri, Namakkal (Part) Krishnagiri, and salem	Calcareous Black, Non Calcareous Brown, Non Calcareous Red,
WesternZone	Tiruppur, Karur (part), Namakkal (part), Erode, Theni, Ariyalur (part), Coimbatore, Dindigul, and Perambalur	Black, Red Loamy,
Cauverydelta	Pudukkottai , Thanjavur, Cuddalore Trichy and Nagapattinam, partsof - Karur, Ariyalur, and Tiruvarur	Alluvium, Red Loamy ,
SouthernZone	Virudhunagar, Tirunelveli Ramanathapuram, Virudhunagar, Thoothukudi, Sivagangai , and Madurai	Black, Deep Red Soil, RedSandy Soil, Coastal Alluvium,
High rainfall	Kanyakumari	Deep RedLoam, Saline Coastal Alluvium,
Hilly	The Kodaikanal (Dindigul) and Nilgiris	Lateritic

Figure 2: Soil Types in Various Agroclimatic Zones

5.1 Data and Method

The proposed study manages to work with heterogeneous data coming from various sources as shown in Figure 3. All the data from the dataset are complementary and characteristic features that are useful for designing and testing machine learning and deep learning approaches. The source of data used in this study are taken from Kendra University of agricultural sciences, Indiastat website, and the soil dataset is collected online from Karnataka soil Health Bhoochetana project ICRISAT, Government of Karnataka. Bhoochetana consists of data from 2013 to 2023.

5.2 Soil Quality Prediction

Farming was a non-technical industry in which methods may be used to improve things. The crop variation makes it possible for the soil to recover nutrients that the crop had previously used and use those resources to grow the new crop.

5.3 Problem Statement

In recent times, IoT has begun to influence almost all industries, including healthcare, power consumption, agriculture, and so on, to reduce inefficiencies in the corresponding field. Smart sensors, handheld platforms, and other IoT devices can be used to achieve effectiveness. Suitable agricultural automation and decision-making may be carried out by utilizing the data gathered through cloud-based data assessments and userinterfaces. Crop health is an essential aspect to consider in modern agriculture for enhanced output. Agricultural specialists must identify and tackle issues in a reasonable timeframe based on an analysis of soil resources and management strategies. The model developed in this study employs deep learning approaches to solve difficulties and improve the accuracy of results for soil evaluation measures.

5.4 Objective of the Research Work

The primary goal of this work is to construct an IoT-based Automated Soil Quality Evaluation using Enhanced Deep Learning Model to aid agriculture in employing IoT and machine learning techniques. This research aims to classify the region based on SQI using sample data collected in and around the districts of Erode and Coimbatore in Tamil Nadu, India. Figure 4 and 5 depicts the agriculture field in Coimbatore and Erode region respectively. The index report was designed for decision-making to offer fertilizer suggestions to specialists based on the categorization findings. Furthermore, the DL-based soil quality evaluation aids in reducing unnecessary fertilizer use and the measurement of soil and ecological sustainability.

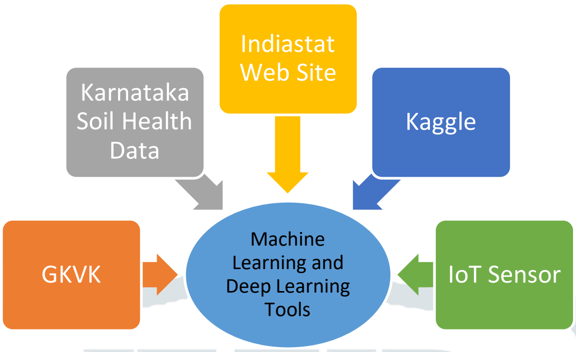

Figure 3: Different Dataset Used

Figure 4: Agriculture Field in Coimbatore

Figure 5: Agriculture Field in Erode

5.5 Need for the Study

There is a need for a transition from a traditional approach to a modern computer-driven approach to enhance the quality of agriculture. Fertilizers provide necessary nutrients for plants that are not available in soil which helps to yield more. Modern agriculture uses IoT technology to calculate the best irrigation schedule and crop watering requirements. This research focuses on ML, DL, and IoT technologies in agriculture applications for crop yield estimation, crop price forecasting, and Image classification for plant disease detection for efficient and sustainable production.

VI. CONCLUSION

This research deals with the survey on general classification, prediction methods, machine learning, and its implementations in agriculture fields. Further, it discussed several techniques, methodologies, and their performance involved in Soil Quality Evaluation and classification. DM is a subfield of ML which concentrates on experimental data evaluation and is sometimes referred to as unsupervised learning. Hence, it is figuring out that the soil quality utilizing Machine Learning techniques. To write efficient implementation code, the utilization of precise programming language. The study reviews digital agriculture and how these innovative techniques can be useful for environmental sustainability and an advanced decision support system for agriculture

4.0. The review presented automation of agriculture which is one of the trending topics and has great future scope. The dataset comprises various parameters whose values are collected using sensors such as temperature, soil moisture, humidity, and soil ph. All these parameters are crucial for plant development. These sensed data are then used for monitoring plant needs and controlling plant growth. The proposed research uses an integrated approach that showed better accuracy compared to all the models discussed in this review.

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