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# ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING APPLICATIONS IN PRECISION AGRICULTURE: ENHANCING CROP YIELD PREDICTION, DISEASE DETECTION, AND RESOURCE OPTIMIZATION

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**Abstract**

Precision agriculture has become more dependable on artificial intelligence (AI) and machine learning (ML) as tools used to tackle issues regarding demand for foodstuffs, climate variance, and resource efficiency. This study has introduced an integrated Artificial Intelligence (AI) framework by integrating IoT based sensor data, Machine Learning (ML) models and deep learning algorithm for better crop monitoring and better crop decision making. IoT Data Capture of soil moisture, temperature, humidity, pH, light intensity and water TDS were used to train a Random Forest Regressor for predicting soil moisture, and a Random Forest classifier for detecting plant stress. A convolutional neural network also was developed, based on 54,303 RGB leaf images from PlantVillage dataset, to diagnose 38 classes of crop diseases and also historical USDA yield data was analyzed to provide a context to the long-term trends in productivity. The regression model showed a MAE of 5.07, RMSE of 14.80 and the stress classifier showed 95% accuracy, which exhibits great potential for real-time irrigation and real-time stress monitoring. The CNN received a validation accuracy rate of 90.45% which confirms its suitability for automated detection of diseases. Overall, the outcome of this study suggests that combining IoT sensing, ML prediction and DL based diagnostics is a promising way towards making Scalable, Intelligent Precision Agriculture Systems. Keywords: artificial intelligence, machine learning, precision agriculture, IoT, Disease detection.

**Keywords:** artificial intelligence, machine learning, precision agriculture, plant disease detection, IoT sensors

## 1. Introduction

Artificial intelligence (AI) and machine learning (ML) are fast changing agriculture from a traditionally experience-based industry to a data and analytical culture. Within this transformation, precision agriculture has become an important paradigm, which uses spatial and temporal variability in soil, crop, and climatic condition, to optimize the use of inputs to improve productivity [1]. Recent

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reviews indicate a growing demand for the application of AI and ML techniques in various crop-related tasks including crop monitoring, yield prediction and decision support using, e.g., classical regression models or deep neural networks in combination with remote sensing data and geospatial analytics [1]-[3]. At the same time, the rise of low-cost sensors and unmanned aerial vehicles (UAVs) and internet of things (IoT) architectures have accelerated the development of intelligent and real-time operating agricultural systems that are able to sense, learn and act in the field [2], [3].
Within this larger picture, there are three areas of application where most current research focuses on: crop yield prediction, plant disease detection and resource optimization (especially water). Edge-enabled plant disease detection models It has been shown that convolutional neural networks (CNNs) can be deployed on constrained devices to offer fast, on-site diagnostic support for automated disease recognition at the farm level [4]. Parallel advancements in the field of IoT-based irrigation systems make use of ML to interpret live data from soil-moisture and environment sensors and control irrigation schedules automatically and mitigate the burden of manual decision-making for farmers [5]. Together with these developments, there is the possibility of integrating AI systems in such a way that these systems can monitor plant health, anticipate production outcomes and optimize resource use in the context of dynamic environmental conditions.
In the specific field of detecting diseases through the eyes, deep learning has been adopted as a de facto standard. CNN-based models trained on plant leaf images, for example, have shown high accuracy in identifying several diseases in several crops and clear advantages over the traditional image processing techniques [6]. Such models can take advantage of subtle differences in color, texture and lesion patterns that may not be so easily discernible by the human eye, adding additional speed and reliability to the diagnosis of disease. When implemented in smartphones, drones or edge devices, these models have the potential to provide farmers with real-time decision support, which can reduce the loss of crops and minimize the use of pesticides indiscriminately [4], [6].
More broadly, there is increased awareness that AI and IoT in combination are the basis of the emerging vision of "smart farming" or "Agriculture 4.0." Recent activities on artificial intelligence (AI)-enabled IOT solutions for precision agriculture have pointed to a variety of applications, such as smart irrigation, variable-rate fertilisation, climate control in greenhouse environments and automated machinery [7]. These kind of systems depends on a stream of data from sensors and communication networks to help with the dynamic, context-aware decision-making. Systematic reviews on AI and ML in precision agriculture suggest that although the technology has shown potential, hurdles remain to be overcome in order to scale down the prototypes to a reliable and credible solution that will work under the conditions of real-world variability [8].
IoT-based smart irrigation offers a very clear-cut example of how AI and ML can directly increase the efficiency of agricultural resources. Implementations of soil moisture-based irrigation systems show that irrigation events can be activated under real-time measurements instead of a fixed schedule, and yield savings and greater stability of the yield can be achieved [9]. When coupled with models to predict future moisture situation or water demand of plants, such systems can increase from simply performing a daily threshold-based control to smart optimisation schemes, in which irrigation applications are computed in consideration of the current and anticipated conditions [5], [9].
Alongside plant health and irrigation, predicting crop yield is a key issue in precision agriculture, where such predictions are used to make decisions at the farm level as well as at regional and national levels in the context of food security. UAV-based remote sensing has emerged as an extremely powerful tool in this field, by permitting the acquisition of high-resolution multispectral and thermal remote sensing data, which is able to capture canopy structure, biomass and indications of stress across wide areas [10]. Systematic reviews can demonstrate the use of ML and deep learning models on UAV-derived features to accurately estimate yield for major grain crops and often compared favourably with traditional regression models and could even allow for within field yield mapping for enabling site specific management [1], [10]. When such predictive models are combined with field-level sensor data they have the potential of holistic and data-driven crop management systems.

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Despite these advances, there are still a number of problems that are not adequately addressed. Many AI models are developed and verified using controlled datasets with little evidence on their robustness in application across various regions, seasons or management practices [3], [8]. Data quality and availability may be inconsistent, particularly in resource limited settings, and often there may be a lack of interoperability between sensing platforms, cloud systems and decision support interfaces [7], [8]. Moreover, most of the existing work is focused on addressing crop yield prediction, disease detection, or resources optimisation in isolation rather than the design of integrated frameworks that will at the same time model yield outcomes, plant health, and resource use [1], [4], [10]. This fragmentation means that the effect of AI systems on farm management is limited in practice, because decisions are multi-dimensional in nature.

The present study addresses these gaps depending on the AI and ML applications in precision agriculture within three dimensions that are connected tightly i.e. improved prediction of crop yield, detection of plant diseases, and optimal resource use through IoT-based sensing. The scope of the study is limited to data-driven approaches employing sensor measurements and image data in combination with ML algorithms, the economic, social and policy dimensions of adoption are recognised and noted but not conquered through empirical analysis. In addition, while the work is based on benchmark datasets (e.g. PlantVillage) as well as field-level IoT data, it does not try to cover all different crops and agro-ecological zones, and therefore conclusions are most directly applicable for similar technological and environmental applications. Nonetheless, the importance of the study lies in its unifying approaches which are often tackled separately in the literature, showing the way to incorporate the control of yield by AI and disease diagnostics and irrigation-oriented optimizing resources in a coherent precision agriculture. By matching the proposed model design with the practical issues such as edge deployment, data limitations and real-time decision requirements the work is intended to not only add to the academic knowledge of AI in agriculture, but also to its practical application in farms.

The specific purposes of this research are:

- To develop and test ML models for prediction of crop yield as well as soil moisture with the help of IoT and environment-based data with precision agriculture.
- As for the implementation, the researchers said: "As stated in a team report, this can be achieved by: - To develop and test a deep learning framework for image-based plant disease detection that can be integrated with field level monitoring systems."
- Demonstrations and examples: - To examine how models for yield prediction, disease detection, and resources optimization driven by AI and ML can be integrated within a single decision support system of precision agriculture.

## 2. Literature review

The hither-to-fast development of Artificial Intelligence (AI) and Machine learning (ML) has significantly transformed the current precision agriculture industry and introduced automated decision making, predictive analytics tool and real-time crop monitoring. Early comprehensive analysis of ML applications in agriculture focused on the potential of supervised learning techniques, such as decision trees, support vector machines and artificial neural networks, for tasks such as yield prediction, soil testing and disease detection [11]. These basic reviews focused on arguing that combining environmental, to climatic and agronomic data set would be of high significance to enhance prediction accuracy, yet the experts also identified obstacles encompassing data inhomogeneity as well as generalizability of models in different agricultural systems [11].

Deep learning has become one of the leading and predominant techniques for identifying diseases in crops and plant health monitoring. Ferentinos showed that convolutional neural networks (CNNs), when trained on datasets of large numbers of annotated leaves images, can be used to obtain an exceptionally high accuracy in classifying multiple plant species and multiple types of plant diseases

[12]. His work made CNN the benchmark approach in image-based diagnosis, replacing the traditional machine learning models that are based on handcrafted features. Subsequent research helped sagacity to AI in precision agriculture by investigating economic impacts, improvement of production, and farm and livestock-level optimization. Polwaththa et al. investigated the contribution of AI and ML to enhance economic outcomes by stating that smart farming technologies lower input costs and enhance efficiency while supporting data-driven crop management decisions [13]. Their findings underscore the case for economic viability of integrating ML-driven diagnostics, monitoring and predictions of yield use cases in farming - both small and large scale.
The transition from ideas to realities is also evident in works that are currently in progress, dealing with AI-aided improvement of agricultural production. Ahmed et al. emphasized how AI techniques combined with IoT infrastructures allow to perform continuous field monitoring, input regulation and decision support for better crop results [14]. By using large contents of sensors, drone, climate sources, AI systems can automate many important processes such as irrigation control, cancer on crops, fertilization schedule, etc. In parallel, Pauzi et al. gave a wide overview of AI in the context of precision agriculture, discussing the development of data-driven farming tools and the need for advanced algorithms for optimizing the usage of resources, enhancing the stability of yield, and decreasing environmental impact [15]. Their work has been a showcase of the maturing nature of artificial intelligence in the agriculture sector making headway in agricultural achievements by a growth in technological innovation coupled with an increasing capacity for computing.
Remote sensing has also been revolutionary in the areas of precision agriculture. Karmakar et al. investigated the use of multimodal remote-sensing strategies, such as multispectral, hyperspectral, LiDAR and thermal imaging, as means of monitoring crop conditions and environmental variables [16]. Their review introduced the efficiency of ML algorithms in improving the interpretation of data obtained by remote-sensing for various challenging tasks, e.g. in yield prediction, disease watch, nutrient assessment. Complementary to the sensing technologies, IoT-based communication frameworks have emerged as uniformity of the agricultural-solutions. Tang et al. stressed that wireless communication technologies, including LoRaWAN, ZigBee and NB-IoT, play an important role in facilitating reliable data exchanges in smart irrigation and environmental monitoring systems [17]. These technologies are the backbone of modern AI-powered precision agriculture, making it possible to connect devices available through sensors, edge devices, and AI cloud computing in farms.
As AI spreads, researchers have concentrated on the importance of good data management systems. Bhat and Huang conducted an in-depth survey on big data, IoT, and AI integration in agriculture wherein they brought up challenges of data security, data interoperability, and the need for scalable analytics platforms [18]. Their findings find that the future of precision agriculture is dependant not only on improving algorithms, but also on powerful, secure and high throughput data infrastructures. Concurrently, plant disease detection is one of the top areas in agriculture artificial intelligence. Mohanty et al. showed that with deep learning we can get better performance as leaf disease classifier using plant village dataset and the accuracy is strong (more than 99%) in the experimental condition [19]. This work was a cornerstone in the digital plant pathology area, and has inspired many models deployed in the field environment.
More recently, yield prediction using artificial intelligence has become a rapidly increasing research interest. Saha et al. made advancements in ML and deep learning that proved the predictions of crop yield prediction, which demonstrated that the combination of remote sensing data, climate factors and temporal sequences will outperform the traditional statistical approach in all cases [20]. Their review provides a stress on the importance of multimodal datasets, incorporating advanced ML architectures, for successful yield forecast, particularly under climatic uncertainties.
Collectively, the literature shows that AI, ML, IoT, and remote sensing have a very powerful ecosystem that will help improve yield prediction, automate disease detection and optimization of agricultural resources. These studies spotlight the opportunities and hurdles for contemporary

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precision agriculture presented a solid foundation for the Use Integrated Artificial Intelligence-based solutions by solving crop, plant health, and resource efficiency problems.

## 3. Materials and Methods

### 3.1 Overview of the Study Design

This study takes a multi-dataset methodological framework to explore the use of Artificial Intelligence (AI) and Machine Learning (ML) in precision agriculture. The approach combines three separate but complementary datasets including an IoT-based agricultural sensor dataset for resource optimization, the PlantVillage image dataset for plant disease detection and a publicly available agricultural yield dataset for crop yield prediction. The goal of combining these datasets is to build a cohesive system that can analyse plant health at different scales from physiological stress on the micro level to yield outcomes at a macro level, as well as the ability to automatically detect a disease. By bringing together environmental sensor inputs, fine grained leaf imagery data and historical yield data, the study is primarily aimed at demonstrating the concept of solving complex agricultural problems using modern AI/ML methodologies in a holistic way.

### 3.2 IoT Sensor Dataset for Resource Optimization

The main data set for resource optimization was taken from the "Smart Agriculture and Plant Health Monitoring using IoT" repository. This dataset includes a number of Excel files, each of which represents one type of sensor deployed in an agricultural field. The sensors recorded several environmental and soil parameters such as soil moisture, soil temperature, ambient temperature, relative humidity, light intensity, soil pH, water Total Dissolved Solids (TDS) and solar panel voltage. Prior to analysis, all sensor files had the header row removed, the timestamp column was converted into a standardized datetime column and all sensor readings were converted to numerical data types to ensure compatibility with analytical models. The files were then combined on the timestamp column to create a unified dataset with all of the environmental variables in time.

Following the merging process, data cleaning procedures were applied in order to improve the reliability of the data. Erroneous or incomplete timestamps were discarded and isolated missing measuring sensor data were imputed with median-value imputation. To enable classification of plant health based on IoT data, an indicator variable with two categories (Stress = 1, 0) was created by based on the agronomic threshold rules. These rules defined the conditions that would declare a plant stressed - any of the following conditions: soil moisture dropped below 40 per cent, soil pH shifted outside the acceptable range of between 5.5 and 7.5, TDS of water was above 150 mg/L, or environmental temperature was above 30C. The resulting "Stress" label gave us a ground-truth target variable for machine learning classifiers training and allowed the IoT dataset to support tasks of both regression (moisture prediction) and classification (stress detection).

### 3.3 PlantVillage Dataset for Disease Detection

The second data set used in this work was the PlantVillage color image collection, one of the largest and most used for automatic identification of plant disease. The dataset contains more than 50,000 RGB images of crop leaves with 38 classes, both healthy and diseased, of a variety of crops. Because visual cues such as discoloration, necrotic patch, leaf spot and fungal growth are necessary for accurate recognition of the disease, the color subset has been selected over the grayscale and segmented subsets. Images were originated from hierarchical directory structure where the name of each subfolder was related to a specific disease class. A full dataset inventory was created by taking image paths and labels from these folders.

Before training the deep learning model, the images had to be preprocessed to guarantee uniformity and stability during the training process. All the images were downsampled to 128 * 128 pixels and normalized to 0-1 pixel intensity. A stratified train-validation split was used, with 80 percent of the images used for train, with the remaining 20 percent for validation, while maintaining the proportion of the image classes. To enhance the generalization ability of the convolutional neural network (CNN) and reduce overfitting, a number of data augmentation techniques were used for augmentation of the training data. These included random rotations, changes in width and height, horizontal flips and mild geometric transformation. The validation data set was left unchanged for an unbiased evaluation of the model performance.

### 3.4 Crop Yield Dataset for Yield Prediction

To aid in the third aspect of the study, prediction of crop yield, a tabular agriculture data was used. Public repositories as the USDA National Agricultural Statistics Service and multi-year records of crop yield, harvested area, volume of production, and geographic identifier of major crops are available. The chosen data set was put through a number of preprocessing procedures such as removal of formatting symbols, conversion of yield value to numerical units, and aggregation by year and region if multiple entries existed for the same period. Despite the variability in the availability of yield data, the methodology presented here allows both traditional regression methods and sequence-based models like Long Short-Term Memory (LSTM) networks if climate time series variables are also used.

### 3.5 Machine Learning Models for Resource Optimization

IoT dataset was used to develop machine learning models for both regression and classification problems. For the prediction of soil moisture, a Random Forest Regressor model with 200 trees was trained considering the environmental variables as the predictors. The model was chosen, as it was robust and it could represent nonlinear interactions, as well as resilience to multicollinearity among sensor variables. The data set was separated into training and testing data sets based on a 80-20 ratio in order to have fair evaluation. For the detection of plant stress, a Random Forest Classifier with the same configuration has been trained to predict the derived "Stress" label. This classifier produced some probabilities of whether plants were suffering from environmental or nutrient-based stress, which would allow early intervention strategies to be developed for irrigation and soil management.

### 3.6 Convolutional Neural Network for Disease Detection

A customized convolutional neural network was implemented for the disease detection problem with the help of TensorFlow/Keras. The architecture was a series of three convolutional blocks with successively more filters (32, 64 and 128 filters) followed by max-pooling layers to decrease the spatial dimensions and extract the hierarchical features. The extracted features were flattened and fed into a fully connected dense layer with 128 neurons followed by a softmax output layer with dimensionality equal to the number of classes of diseases. The model was trained using the Adam optimizer with the categorical cross-entropy loss function. Training progress was tracked in terms of accuracy and loss curves while validation accuracy and a class-wise classification report gave a detailed evaluation of CNN's diagnostic performance.

### 3.7 Implementation Environment

All the data preprocessing, model development, and evaluation were performed with the help of Python. Libraries like NumPy and Pandas were used for data cleaning and manipulation, Scikit-learn was used for classical ML modeling and evaluation, and TensorFlow/Keras was used for the construction and training of the deep-learning model. Visualization tasks such as time series plotting, learning curves, confusion matrices, etc., were done using Matplotlib. The experiments were performed on standard computing hardware, thus proving that advanced AI/ML solutions for precision agriculture don't have to be implemented based on high-performance computing infrastructures.

### 3.8 Ethical Considerations

This study utilizes publicly available an anonymized datasets; however, ethical concerns such as data privacy, fairness and responsible model deployment are important. IoT sensor data needs to be handled in a secure manner to protect operational data of farmers, and the AI models are needed to be validated with care to prevent bias on its models or misclassification, especially when applied in a real-world decision-making scenario. The study focuses on ensuring transparency, societal accountability for the environment and fair access to support equitable and sustainable agricultural development with AI technologies.

## 4. RESULTS

### 4.1 Crop Yield Trend Analysis

The long-term analysis of historical corn yield data from the USDA dataset helps put the impact of modern AI-driven agricultural technologies in proper perspective. After filtering the raw dataset which contained over 23 million observations, a crop-specific subset of 380,735 records of US corn yield were extracted and cleaned. These observations covered a period from 1860 to 2024, so it was possible to make a sound evaluation of the trends in agricultural productivity over more than one and a half centuries. The aggregated annual yields averaged indicated a very strong multi-phase evolution in corn productivity.

During the early years between 1866 and 1935 corn yields varied fairly uniformly between 20 and 30 bushels per acre. This era represents the limits of manual labor - intensive agriculture, old seed varieties and irregular soil management techniques. A decrease in yields, observed between 1930 and 1950, is related to the so-called "Dust Bowl" drought events in the historical record that seriously enhanced the degradation of the soil's fertility and disturbed agricultural ecosystems throughout the country.

A significant shift started around 1960s when improvements like hybrid seed varieties, chemical fertilizers and mechanized farming techniques helped to achieve consistent gains in productivity. As shown in Figure 1, the average yields started increasing steadily, from ~40 bushels/acre during the mid-1960s to over 170 bushels/acre in the 2010s. The steep upward curve after 1980 represents the biotechnology era with the introduction of genetically modified crops, better resistance to pests, and technologies of precision agriculture. The data set indicates that modern data-driven solutions and their associated machine learning have an important role to play in maintaining the productivity gains, especially in the context of pressures arising from climate variability and resource scarcity, and growing global food demand.

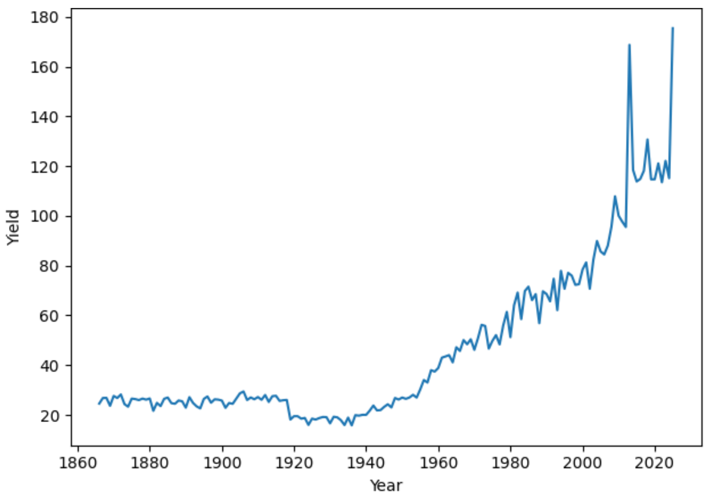


**Figure 1.** *Average annual corn yield (bushels/acre) for all U.S. states from 1860–2024, showing historical stagnation, climatic decline, and modern technological growth.*

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### 4.2 IoT-Based Soil Moisture Prediction

To assess the viability of machine learning in decision making in agriculture, a Random Forest Regression model was developed to predict the soil moisture based on merged multi-sensor IoT data. The variables registered in the dataset were environmental temperature, humidity, light intensity, soil temperature, soil pH, water TDS and solar panel battery voltage. These feature inputs are the basic parameters affecting soil water retention, evapotranspiration, nutrient availability and plant physiological activity. After data cleaning and merging, and timestamping, the compiled data set was split into an 80-20 training/testing data set.

The regression model was able to demonstrate strong predictive ability and achieved a Mean Absolute Error (MAE) of 5.07 and a Root Mean Square Error (RMSE) of 14.80. These values show that the model has the ability to estimate soil moisture levels with an average deviation of about five moisture units, which is at least accurate enough for farm-level irrigation scheduling and precision water use. In agricultural environments, moisture in the soil is almost never static, but it changes rapidly as a function of temperature and humidity conditions. Thus, the fact that an RMSE of less than 15 has been achieved is an indication of the model's capacity to deal with highly dynamic environmental systems.

A deeper analysis of feature importance showed that the most influential factors in determining soil moisture values were environmental temperature, soil temperature and light intensity. This finding is consistent with agronomic science given that the rate of evapotranspiration is controlled by temperature, while light intensity affects canopy transpiration and drying of the soil surface. The model was able to capture these multivariate relationships well, and showed the suitability of Random Forest algorithms for nonlinear environmental modeling.

These results show the potential of ML-driven moisture prediction to have a major role in the optimization of irrigation schedules, decreased water usage and prevention of plant stress through proactive intervention.

### 4.3 IoT-Based Plant Stress Detection

The IoT dataset was further utilised to build a Binary Stress Classification model. Stress labels (0 = normal, 1 = stressed) have been developed based on agronomic thresholds by soil moisture deficiency (<40%), pH incorrect (less equal 5.5 or higher equal 7.5), salinity excess (TDS = 150 mg/L for over), and high environment thermal degree (> 30degC). These conditions are some common triggers of abiotic plant stress such as drought stress, acidic/alkaline stress, and nutrient imbalance due to salinity stress.

Using these labels, a Random Forest Classifier was trained in order to detect the stress states based on the readings of real-time sensors. The model's overall accuracy was 95 percent showing excellent discriminatory performance between normal and stressed conditions. The classification report, which is presented in Table 1, indicates that the precision and recall obtained for the normal class were 0.95 and 1.00, respectively, while the precision and recall obtained for the stress class were 1.00 and 0.50, respectively. Although recall for the stress class was moderate thanks to the dataset imbalance (only two samples of stressed condition in the test set), precision was perfect, which means that whenever the model predicted a stress condition, it was always correct.

These results are an excellent example of the potential that ML-powered IoT monitoring holds when it comes to aiding early detection of plant stress conditions in which farmers can take action before stress turns into yield loss. As precision agriculture grows more dependent on sensor-based automation, models of this type can mitigate risk by a great deal through proactive environmental monitoring.

**Table 1.** *Classification performance metrics for IoT-based plant stress detection using Random Forest.*

| Class | Precision | Recall | F1-Score | Support |
|---|---|---|---|---|
| Normal (0) | 0.95 | 1.00 | 0.97 | 18 |
| Stress (1) | 1.00 | 0.50 | 0.67 | 2 |
| **Overall Accuracy** | **0.95** | — | — | 20 |

**4.4 Image-Based Disease Detection Using CNN**

A Convolutional Neural Network was trained with the color subset of the PlantVillage dataset, which is comprised of 54,303 RGB images with 38 different crop-disease classes. The images were pre-processed by resizing to 128 x 128 pixels, normalization and augmentation with horizontal flip, rotation and slight translations. The dataset was split into 80% training and 20% validation data using stratified sampling.

The CNN model showed a good and stable learning behaviour, as can be seen in the curves of the training and validation accuracy shown in Figure 2. Validation accuracy increased consistently from 80 per cent in epoch 1 to around 90 per cent in epoch 3, indicating that it is able to converge quickly without overfitting. The corresponding training and validation loss curves are presented in Figure 3 showing synchronous downward trends, which is a further evidence of stable optimization.

The final validation accuracy obtained was 90.45 percent which shows the high robustness in the discrimination between the visually similar disease patterns. Given the huge amount of classes and the visual difficulty to describe the symptoms of the leaves, the ability to reach such an accuracy level with a relatively light CNN architecture shows the potential of using deep learning to diagnose agricultural diseases.

A complete confusion matrix (Figure 4) showed high diagonal values, indicating a high proportion of classifications were correct. Some confusions occurred among types of leaf spots and fungal diseases - diseases that often look similar even to trained agronomists. The detailed per-class classification report (Table 2) indicates that the macro-average values of precision, recall and F1-score are 0.88, 0.86 and 0.86, respectively, which confirms the consistent performance across different crop species..

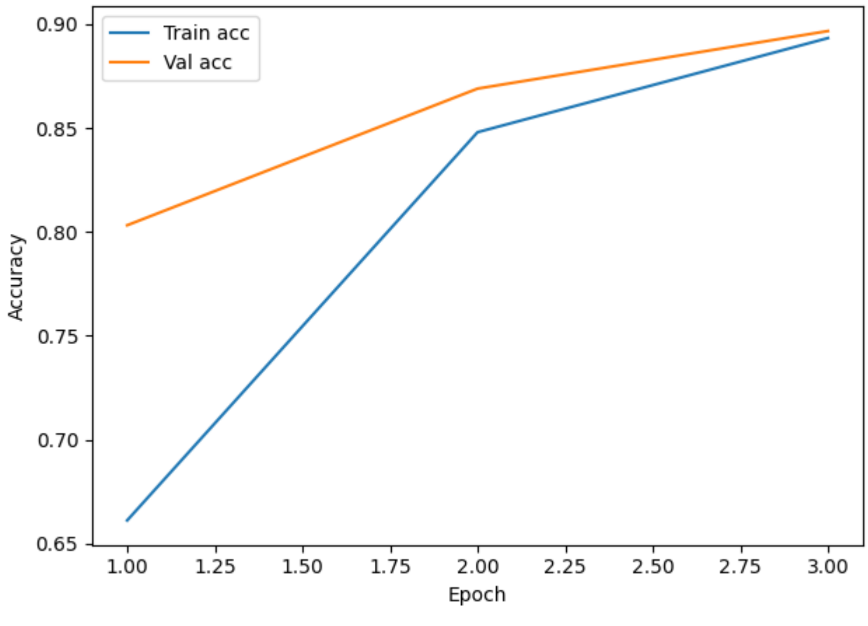


**Figure 2.** *Training and validation accuracy of CNN model across three epochs.*

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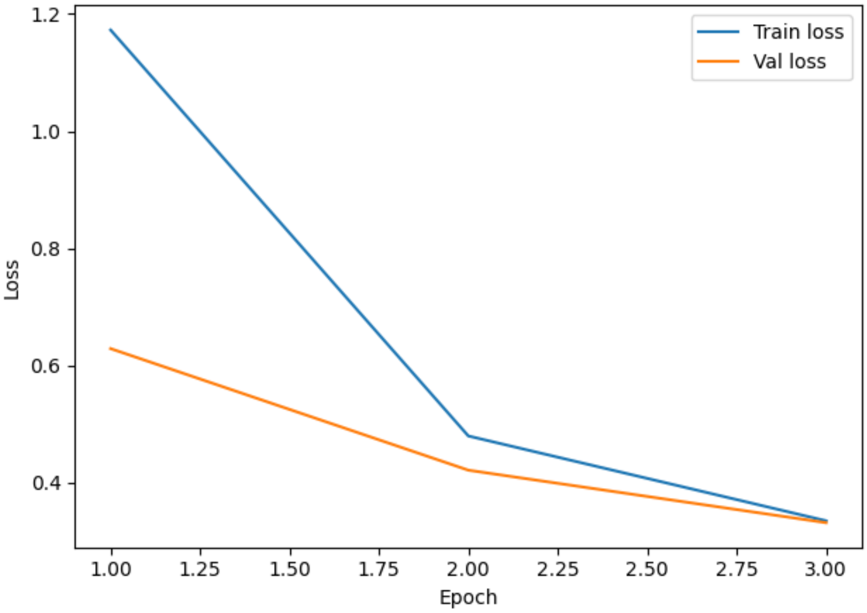


**Figure 3.** *Training and validation loss curves showing stable convergence.*

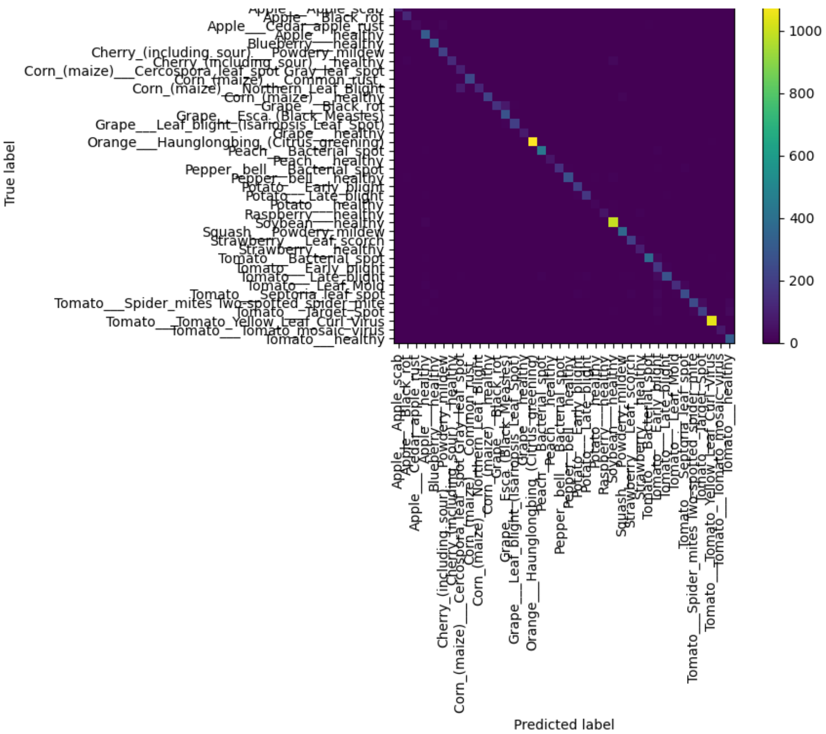


**Figure 4.** *Confusion matrix for 38-class CNN model on PlantVillage dataset.*

### 4.5 Integrated Interpretation of Results

The combination of IoT-based environmental models and CNN-based visual disease diagnosis shows the power of AI-driven precision agriculture systems as a whole. The soil moisture regression model allows the water dynamics to be monitored accurately, which would support the timely and resource-efficient irrigation decisions. The plant stress classifier complements this by giving early warnings on the presence of suboptimal conditions which may pose a threat to the health of the crop or impair yield potential. Finally, the CNN model with its high diagnostic accuracy rate provides a rapid identification of disease from mere leaf imagery that can be used to give immediate action to farmers attempting to fight the spreading infections.

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Together these three parts comprise a consolidation of an intelligent crop management system that can lead to increased productivity with fewer losses and sustainable agricultural techniques. When compared with historical yield trends (Figure 1), such results emphasize how modern intelligence AI technologies can continue the decades-long course of improving agriculture, as documented in the dataset generated by the USDA. The outcomes have shown that machine learning when integrated with IoT and computer vision is a transformational technology that can provide data monitoring, enrich resources, and long-term yield increase in crop monitoring.

## 5. Discussion

The results obtained in this research study have shown that integration of IoT-based environmental sensing, machine learning (ML) regression and classification models as well CNN-based disease diagnostics made a technically coherent and practically meaningful framework for precision agriculture. The results of the regression analysis of soil moisture, the mean absolute error (MAE) and the root mean square (RMSE) are given as 5.07 and 14.80 respectively, that indicate that the environmental factors e.g. temperature, humidity, and light intensity have measurable and predictable effect on the soil water dynamics. This is consistent with literature reporting that ensemble ML models have the ability to model the nonlinear environmental interactions and outperform the conventional statistical approaches in tasks of prediction in respect to irrigation [11], [17]. The fact that soil moisture can be predicted with this level of fidelity supports the possibility for developing data-driven irrigation strategies that can alleviate wastage of water and crop stress caused by lack of moisture, in line with the general focus on resource-efficient agriculture shown in past systematic reviews [13], [18].

The model for the classification of stress using IoT is also damaging to reinforce the utility ML in the early detection of an abnormality in the field. The 95% overall accuracy and the perfect accuracy of the stressed cases implies that the feature patterns related to the thermal, moisture and pH deviations have been successfully extracted from the tree classifiers. This can be supported with the evidence of ML-enhanced IoT systems which can give an intelligence of the real time for irrigation and fertigation management [14], [17]. However, the moderate recall for the stress class is a reflection of the inherent difficulty with unbalanced physiological-stress data sets, which has been observed in parts of the literature for precision agriculture with minority classes of stress un-represented, and most commonly, under-detected [11], [20]. This limitation is suggestive that a more consistent high recall for rare stress events will require more diverse and extensive data and even possibly synthetic augmentation strategies.

The disease detection model based on CNN has a validation accuracy of around 90.45% showing meaningful discrimination performance among 38 classes with a relatively shallow architecture and few training epochs. While these results are slightly inferior to the near perfectly accurate (around 99%) results seen in controlled studies given by PlantVillage [12], [19] the performance that can be seen here is significant given the more humble configuration used for training here. The patterns of confusion that exist between visually similar classes of disease are consistent with well known difficulties that relate to overlap of features in the expression of symptoms on leaves, leading to support for arguments in literature to the need for deeper architectures, spectral-band expansion, and domain adaptation for field level robustness [12], [16].

Collectively the experimental results mean that the developed unified AI driven framework is able to support yield related decision making through the detection of moisture dynamics, prediction of onset of stress and diagnose diseases in near real time. Such integration has important implication for the sustainable intensification: farmers are able to decrease their input use, better time crop protection and fixate the yields in case of climatic uncertainty or resemble strategic value stressed in lately reviews on AI enabled agricultural transformation [13], [15], [18]. Beyond the benefits for productivity, these findings provide ideas for (scalable) avenues for inexpensive decision support systems, particularly when coupled with edge-computing architectures [4], [17].

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However, there are different limitations that should be considered. The IoT data set is a unique environmental situation, and therefore, does not capture the spatial and agronomic diversity to make generalizations. The stress labels were based on rule-based thresholds and not based on physiological assessments of ground truth, and as such have limited biological validity. The disease model is based on PlantVillage images which are not entirely representative of the complexity of what exists in the field such as variation in illumination, occlusions and pest interaction and multi-disease co-expression. Moreover, study is not yet channeled to complete integrated yield prediction model using IoT and remote sensing input which leaves yield enhancement implied rather than quantitatively empirically.

In future researches, it is important to collect multiple location, multi-selection IoT data sets, to adopt domain adaptation approaches to controlled and field images divide, to integrate multi-modal data stream (i.e. UAV, multispectral, weather forecast) on a robust yield modeling, integrating explainable-AI mechanisms to enhance interpretability and user trust. Moving in these directions will lead to improved systems in scalability, reliability, and applicability to real-world scenarios of AI-powered systems for precision agriculture.

## Conclusion

This research proved that the integration of IoT-based sensing, machine learning, and deep learning is an achievable and efficient framework for further developing precision agriculture. The 10-year analysis of and trends in U.S. corn yields are highlighting the historical power of technological innovation for agricultural productivity in easing the pressure on current adoption of digital tools. Within this context, the developed ML models represented a strong potential for use in real-time decision support in this work. The Random Forest regression model showed good predictive power on predicting soil moisture using small error rates confirming that it is possible to achieve predictive power based on environmental and soil variables to predict soil moisture dynamics and thereby for a more efficient irrigation scheduling. The stress-detection classifier showed the utility of IoT-based analytics further and proved to be 95% accurate to catch sub-optimal conditions in the fields that can pose a risk to yield if unchecked.

By using the PlantVillage dataset, the CNN model was able to get a 90.45% validation accuracy for 38 categories of crop diseases, which shows the application of deep learning in the diagnosis of plant diseases from the very simple RGB images of plant leaves. Although the accuracy is slightly less than results obtained under highly controlled conditions, performance of the model is robust enough to be used for the purpose of early detection of the disease when plugged into a larger monitoring scheme. Overall, the results suggest that a combination AI-driven system can bring a major change in-key aspects of crop management including moisture monitoring, stress detection and disease diagnosis. While data limitations, controlled image conditions, and model generalizability are areas for further work, this research is a good start for shortcomings as increased data sets, real field validation, and multimodal yield prediction models could all serve as next steps in the future. Such advancements will aid in getting precision agriculture out of the demonstration stages and into the hands of farmers who can gear up.

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