International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 1, 2025
https://www.theaspd.com/ijes.php

AI-Driven Predictive Modeling for Crop Disease Detection

Dr. Stuti Asthana[1] and Dr. Rakesh Kumar Bhujade[2]
[1]Independent Researcher and Analyst, Fortune World, Near Government Degree College, Nani Daman, Daman UT, India, Pin 396210
[2]Department of IT, Government Polytechnic Daman, Mota Falia, Nani Daman, Daman UT, India, Pin 396210
Corresponding Author: rakesh.bhujade@gmail.com

Received: 21st July 2024
Revised: 04th November 2024
Accepted: 25th December 2024

Abstract: *The efficient and safe production of crops is critical to addressing global food security challenges, which are exacerbated by rapid population growth. Among the numerous factors affecting agricultural productivity, plant diseases play a significant role in hindering crop yields. The accurate and timely detection of these diseases has become a pivotal area of research. Geographic Information Systems (GIS)-supported farming information systems have emerged as a powerful alternative to traditional farming methods, enabling more precise decision-making by overcoming the limitations of human-based approximations. Data mining (DM) techniques have been widely adopted for crop disease detection, leveraging large volumes of agronomic data to uncover hidden patterns and predictive insights that humans might overlook. Despite extensive research, some emerging technologies still show relatively lower success rates in diagnosing certain crop diseases. To address these challenges, Artificial Intelligence (AI) and Artificial Intelligence Recognition (AIR) models have been proposed as promising solutions. By utilizing hyperspectral imagery generated through AI-based pattern recognition, these models can detect specific crop diseases, such as head blight, with an estimated 70% accuracy. This approach represents a significant advancement in agricultural disease detection and forecasting, contributing to more efficient and sustainable crop management practices.*

Keywords: *Geographic Information Systems (GIS), Data mining (DM) techniques, Artificial Intelligence Recognition (AIR)*

1. INTRODUCTION

Optimizing the efficient and safe production of crops is pivotal for addressing the global food security dilemma, a situation accentuated with rapidly expanding population growth. Among the various factors influencing agricultural performance, plant diseases, as a counterpoint, have adverse impacts. Consequently, the efficient and accurate detection of crop diseases has turned into a crucial research focus. The global synthesis of GIS (Geographic Information Systems)—supported farming information has engendered liberation from traditional farming feasibility studies, which were based on the conclusions from approximations and detailed insulation time between the human outcomes process. Data mining (DM) is a widely utilized tool for crop disease detections and has the ability to process a considerable volume of agronomic data. It also recognizes concealed and predictive-related knowledge that is not feasible for a human being over vast geographic farming data. So far, plenty of literatures have probed these technologies in various crops for disease detections. However, it was perceived that some novel technologies have comparatively lower success rates when employed in the diagnosis of similar crop diseases. Therefore, a model using AI and AIR can be addressed to tackle these constraints. Factitiously generated imageries created from hyperspectral bands can be applied to develop computer-aided pattern recognition models known as AI in order to detect plants infected with the head blight disease. This generated computer model can be used to predict infected crops in upcoming years with 70% success. Furthermore, actual observation on-ground stations can assess the model's performance on a year-by-year basis [1].

2. BACKGROUND

The goal of farming, from ancient times to today, remains cultivating crops. To ensure good crops, nutrients are provided in the form of artificial fertilizers. However, their excessive application can lead to nutrient depletion in the soil. Using advanced technologies, such as drones or robots, the deficiencies in the fields can be spotted early and rectified. Furthermore, an AI-based model can predict the crop diseases and suggest remedies. This would help prevent a crop epidemic and reduce the use of pesticides. Crop management with such technology would lead to high yield and quality crops with a lesser impact on the environment. With the evolution of modern agriculture practices and the advent of precision farming, the accurate and efficient detection and diagnosis of crop diseases have become a crucial concern and research topic. In developing countries the agriculture sector supports a major fraction of the economy, and the majority of farmers are smallholders. Providing these smallholder farmers with the knowledge and tools to support their decision-making processes across planting, harvesting, and protection would not only uplift their financial well-being but also be beneficial from a more general perspective. Thus, research in the context of providing a feasible solution using modern, sophisticated systems and approaches involving the integration of several components is emphasized. Regarding that, the AI-based prediction model to predict the crop diseases in advance is proposed to farmers. The model would forecast the occurrence of diseases and suggest causal agents to minimize the damage [1].

2.1. Overview of Crop Diseases

Plant diseases affect a variety of agricultural processes and food safety problems associated with plants. Plant health and food safety are closely related. Plant diseases are an act to disrupt important activities by interfering with their normal state. This leads to poor growth, abnormal appearance, and reduced yield in plants. It is also responsible for destroying the supply of fruits, vegetables, and cereals to communities, and in some instances as sandwich bread, resulting in the development of quarantines in society. Some plant diseases have the ability to spread rapidly and infect nearby crops. The prevention and identification of plant diseases is instrumental in healthy growth. Plant diseases are caused by several factors, such as viruses, fungi, and insects. Various methods are used to identify plant diseases.

2.2. Importance of Early Detection

User has proposed an AI-driven predictive modeling method for early crop disease detection by integrating artificial intelligence and physical process modeling technologies. The modeling framework includes three modules. First, an LSTM model is implemented to predict future weather conditions based on historical weather data. The predicted weather information is then used as the input for a crop disease spreading model which is implemented using susceptible-infectious diffusion processes. By solving Laplace's equation in a rectangular field which is derived and numerically approximated, the likelihood of infection of each grid within the field is calculated. The methodology can assist farmers in preventing the spread of crop diseases efficiently and is highly applicable to a crop grown on a large scale. In addition to diminishing yields, they also adversely affect the overall crop quality. Previous research studies estimate that, on average, crop diseases destroy between 10% and 25% of potential crop production annually, which would otherwise be enough to feed 1.5 billion people. Uncertain and highly changing environmental conditions create optimal environments for pathogens to infect crops.

2.3. Current Methods of Disease Detection

For the modernization of agriculture, cultivation robots and drones have developed rapidly and begun to be widely applied in practice. At the same time, deep learning technologies have also shown excellent performance in processing and analyzing big data. To facilitate the research, a collection of databases of natural crop images infected by diseases were established. Notably, multiple pretrained models were made available for download and fine-tuning.

3. ARTIFICIAL INTELLIGENCE IN AGRICULTURE

Artificial intelligence (AI) is a major field of the 21st century, and the main goal of using intelligent systems in various fields is to enable them to make highly precise decisions or predictions based on the current conditions or situation. In this process, the underlying mechanisms or a model that quantitatively describes the problem are trained with an unseen data set, and therefore, it is possible to generalize the intelligent system for various situations. AI provides computational intelligence such that a machine can learn, understand, and respond to varying situations. Based on this computational intelligence, various problems in the real-world environment have been addressed in many ways. In the course of time many more data will evolve because the combination of IoT sensors and camera embedded drones produces millions of data points diligently for each day. This big data must be transferred to a cloud and we must infer the meaning of this big data generated over time with the help in AI [3].

3.1. Role of AI in Crop Management

Artificial Intelligence is recognized as one of the major technologies of the 21st century. It is adopted in many a modern application to make intelligent and precise decisions based on the condition of the tasks. Agricultural Dome is one of them. Traditional methods used in the agriculture domain are based on experience and have many drawbacks due to non-precise decisions. Modern/AI-based methods provide computational intelligence as the human thinking and decision-making process is an input for machines and results in analysis for proper and intelligent actions. In the agricultural domain, millions of data points, including environment and crop growth conditions, are acquired daily as data streams and data records by using IoT sensors and UAVs in the field. Farmer machines only make intelligent and timely decisions on the field task by analyzing big data on the cloud. Precisely, farming is the key pillar of AI-driven agriculture domain applications, making a proper decision by predicting the affairs of interest in the agricultural device and acting on that in a timely and proper manner.

3.2. Machine Learning Techniques

Given the importance of crops in agriculture, approaches for predicting the risk of crop diseases have mainly focused on an easily identifiable phenomena such as large-scale defoliation caused by severe outbreaks of a foliar fungal disease [4]. Small-scale damage of crops by pests and diseases has usually been monitored manually, but with recent developments in sensors, it is now possible to monitor the crop environment in real time. Along with the rapid development of AI, many researchers develop AI-based predictive models as an alternative approach to lob that a numerical disease risk can be predicted using sensors. Pests and diseases are regarded as potential hazards for crops, therefore great attention has been paid to the study of pest and disease prediction models [1]. Using this approach the risk of the occurrence of pests and diseases is estimated for next day in terms of the accumulated risk factor.

3.3. Deep Learning and Neural Networks

Deep learning encompasses high-level levels of neural networks in a multi-layered framework and mimics the structure and function of the human brain. Deep learning has been found to outperform typical machine learning processes in a variety of tasks. It has been shown that deep learning algorithms, including deep convolutional neural networks and stacked autoencoders, can be effectively applied in agricultural engineering. In various labor-intensive agricultural functions, this technology can help in minimizing human intervention and increasing output. It has potential for crop yield prediction, disease discovery, and pest prevention.

Modern farms have been using unmanned aerial vehicles, or drones, that can showcase cutting-edge agriculture technology for the diversified development of agriculture since they can monitor farmland continuously and detect diseases in crops or plants through high-quality photos and other monitoring equipment. UAV technology has a substantial potential to develop digital farming on numerous fronts. Due to current technological advances, farm systems empowered by UAVs and data analytics are on the rise. Field-based phenotyping through array approaches is one the forefronts of scientific advances in agriculture.

4. PREDICTIVE MODELING TECHNIQUES

Machine learning-based predictive modeling techniques have been proposed to detect crop disease accurately. A deep learning model has been developed for predicting risk probability scores of crop pests and diseases based on sequential meteorological variables. It applies an ensemble network that combines an attention mechanism which uses prior likelihood obtained from handcrafted profiles and a neural network that extracts features from sequential input data. The proposed model can support policy decision-makers or farmers by providing the risk scores of crop pests and diseases.

In agriculture, the estimation of crop diseases is a significant task for strategic farming and sustainable cultivation. The maintenance of crops is a basic requirement for keeping animals and humans alive, and the yield value of agricultural products is crucial to food security and gross domestic product. Many researchers have inspected the potential prospective for recognizing and forestalling the hazards affecting the crops, such as pests, and diseases, where it is known that the meteorological variables have some impacts on the cultivation of crops. Concerning this, a deep learning model for computing the prospects of crop pests and diseases is proposed [4].

The ensemble network consists of two networks: an attention generating network and a feature extracting network. The attention network computes the probability score of the sequential meteorological templates. The feature network features of sequential meteorological inputs. The attention scores are multiplied by the extracted features and petiolar.

4.1. Introduction to Predictive Modeling

The ongoing use of computers and sensors in the storage environment of crops, which have flourished since 2020, provide a macroscopic record of plant growth environments such as light, humidity, and room temperature, enabling post-analysis of crop environments on a large scale. However, modeling approaches that predict pest infestations with only growth environment information are currently rare. Most models for crop diseases and pests require post-processing of leaf images or only predict upon acquiring new data. A modeling approach is introduced to predict the risk of pest infestation in crops based on growth environment data and calculate a linear risk score. This work does not use agricultural chemicals as features and tries to predict the risk of pest infestations of crops with only growth environment information using deep learning. An overview of this study is as follows. A method to build a crop disease onset prediction model using growth environment data learned from multiple facilities is described.

4.2. Hidden Layer Architectures

Deep learning has tremendously improved the field of machine learning and computer vision. Usage of deep learning in the agriculture sector has, nonetheless, been an developing field recently, in which Convolutional Neural Networks (CNNs) have been greatly engaged. By utilizing CNN architectures, exploration in the agriculture sector has considerably enhanced prognosis accuracy in the identification of herbal diseases. A new problem formulation is being addressed inspired by these developments. More specifically, the key objective address by this work is to refine, classify, and comprehensively evaluate the architectures of the hidden layer for pictorial plant diseases.

Recently, [5] have proposed a novel method of detecting diseases in tomato and corn leaves using computer vision and deep learning. With a publicly available dataset that collectively contains 1250 images of disease-infected and healthy leaves of tomato and corn plants, 7 different CNN-based models are evaluated.

4.3. Model Training and Validation

Several models were developed to predict strawberry disease outbreak through deep learning, including a base model, a second model with attention, and a final model using data resampling and model ensemble. Korea's precipitation and crop damage data were used to create the dataset for the model. The dataset is daily for each data and includes the continuous precipitation for the last certain month. Crop damage data are classed as the output class of the model, each class corresponding to a certain extent of crop damage. Three models are created: a base model, a model with attention, and a final model using data resampling and model ensemble. The disease outbreak condition in strawberry under light conditions can be predicted almost 2 days in advance. The proposed methodology in this study can also be applied in practical applications, like a smart farm, to prevent crop disease. The smart farm continuously monitors the environment to grow crops and takes early precaution against disease outbreak of the growing crop [4].

5. DATA COLLECTION AND PREPARATION

The present study seeks to develop a generalizable high-accuracy rice disease detection model and proposes a novel method for the least-reported fine-tuning process in CNN. This involves phase-by-phase unfreezing and gradually retraining of the CNN layers while strengthening the regularization to prevent excessive tuning of the model on limited in-domain data. Additionally, images of crops and rice disease commonly hidden in a greenhouse are proposed for the first time, together with a comprehensive list of representative visible/invisible and anatomical symptoms, to extend the scope of the image dataset and associated research directions. Since climate conditions underpin the occurrence of pests and diseases, a compilation of frequently used libraries and a step-by-step practice guide to local real-time environmental data for model training are presented, which is expected to motivate and facilitate other researchers to delve into this interdisciplinary topic.

5.1. Sources of Data

Model-based systems have been on the rise across all sectors, including applications in agriculture. In recent years, researchers have begun utilizing artificial intelligence (AI) methods to construct model-based systems to undertake fundamental tasks in agricultural monitoring, such as prognosis and diagnosis of crop diseases [4]. Extensive studies have investigated AI-driven predictive models for crop disease estimation. These models can predict the risks or likelihood of crop diseases being present in future periods, based on existing data. Such systems have great implications in helping farmers adopt corresponding preventive measures in advance. The innovation advances understanding of the dynamics of agricultural systems and benefits timely intervention methods toward the sustainability of agriculture.

5.2. Data Cleaning and Preprocessing

Data cleaning and preprocessing involves several steps. The data was removed such that the number of features increased to 52, and a 5 min buffer after the rising/falling time of the condition label was established. The sensor data for each condition instance was normalized according to its time window such that the training was conditioned to the mean and standard deviation. The libraries were used to build the model and conduct the experiment. Support for large, multi-dimensional arrays and matrices and a variety of mathematical functions were provided. Data manipulation and data analysis tools were utilized, and data structures were built on top of the array library. It is expected that within the same training 5 min buffer, as the sensor data is the same for all the conditions, the crucial features are also the same, irrespective of the condition label. This expectation is based on the same methodology in similar situations. After normalizing for each condition instance, to the mean and standard deviation within its 12-hour time window, it is anticipated that irrespective of all condition instances, the same model for any given time window is yielded.

5.3. Feature Selection

Feature selection is an essential aspect of predictive modeling. Statistically significant and qualitative results can often be rendered. A dataset must be thoroughly analyzed in order to select the most appropriate features. As a beginning, univariate feature selection is led by the analysis of variance test. The crop disease and environmental data are gathered from the datasets previously used for crop disease and growth forecasts and are named the crop disease dataset. An comprehensive evaluation and analysis of the predictive results follow the proposed predictive modeling approach in order to determine the impacts and importance of crop disease and environmental factors on future work. Each dataset feature is considered as the capped independent variable, while Crop_Disease_Status is the dependent variable. Univariate feature selection was carried out on the crop disease dataset as a preliminary step to distinguishing the most significant features for the dataset. The f_classif is applied here as a univariate feature selection approach [6].

6. IMPLEMENTATION IN RESOURCE-CONSTRAINED ENVIRONMENTS

Successful implementation in resource-constrained environments necessitates reliability, ease of access, and compatibility with mobile devices. This presents an AI-based model for crop disease classification integrated with Raspberry Pi for deployment on resource-constrained IoT devices. The popular crop diseases of Maize crop are utilized for the classification task. Attention-based feature extraction inspired by Vision Transformer with the popular Support Vector Machines classifier are applied for disease classification purpose yielding an accuracy of 99.69 for the unseen dataset.

The model is quantized and converted to TensorFlow Lite format for integration with an IoT device. The quantized model achieves an accuracy of 97.41 and can be deployed on IoT devices like Raspberry Pi 4. Plant diseases have long been a source of concern for agricultural productivity, leading to a considerable decrease in crop yield. By focusing on all parameters that influence the readiness of a smart agriculture system, the following considerations were made: i) the AI model must be available for farmers as a mobile app; ii) the model must be compatible with both Android and iOS devices, thereby ensuring that the model is user-friendly; iii) the ideal proposed model must be trained on an AI platform that supports the exporting of models in a specific format that is amenable to integration with an intended IoT, and; iv) the model must be able to run on the IoT device to fit into the hardware limitations. Consequently, the AI-based model was developed for crop disease classification. In order to achieve higher predictive performance, robust Attention-based feature extraction inspired by Vision Transformer is employed, paired with the popular Support Vector Machines technique. In turn, the SVM classifier is adopted for plant disease classification due to its simplicity and effectiveness.

6.1. Challenges in Resource-Constrained Settings

Crops are the primary source of energy, nutrition, and medicinal to dilapidated human beings. During harvesting crops, deterioration of leaves by plant diseases is common which causes a heavy loss on crop yield as well as economic value. It is very important for farmers to identify diseases and take remedial measures to prevent the epidemic of the diseases. Identifying plant diseases immediately can save research. Therefore, it is requested to the agriculturist or the students who are interested in the agriculture field must be familiar with the symptoms of the different plant diseases on no taken. One in-depth review of the popular studies of ML and DL-based methods for diagnosing plant diseases is presented in this document. A novel method for classifying crop diseases is also proposed using a unique combination of support vector machines (SVM) and attentional feature excavation for disease identification of smartphone-captured leaf images by joining an innovative Green Chromatic Coordinates (GCC) and lighting and undertone image attributes to normal convolutional neural network (CNN) modeling of filling in the Karomi and Plant Village data sets and a public database plant leaf data set [7]. This proposed model is used solely for SVM classification and is then transformed into a mobile-integration classification design (mPD-App) capable of operating edge devices for indoor or on-field use by utilizing the specialized vision transformation block and attention-based machinery of the disease-extracted signage (mPD-APP) [8].

6.2. Optimizing Model Performance

Crop diseases have always been a major concern of farmers, seriously affecting the quality and yield of crops. At present, the main way to detect diseases and pests is to have people check and analyze them with the naked eye, which is time-consuming and labor-intensive. There are certain limitations when the number and density of infected parts are higher or the internal pathogen causes no significant difference on the surface of the plant. Furthermore, after the disease is discovered, the spread of the disease cannot be completely prevented. In addition, the late eradication effect is generally low, resulting in serious crop yield reduction, and some diseased plants infect others, resulting in aggravated losses.

Medical, financial, and commercial industries have recently applied artificial intelligence models to forecast something in the future. In the agricultural field, scholars also use the model to help people check whether the product is safe to eat. For validation methods, K-fold cross-validation was performed to obtain better test results when tested on unseen data. In addition, researchers also tested 15 various leading pre-trained deep learning artificial intelligence models to get the best artificial intelligence model and reduce the time that researchers first spent developing the model [10].

6.3. Case Studies of Successful Implementations

Deep learning has demonstrated promising results in various fields like computer vision and speech recognition. In recent years, researchers have begun to deploy these models to identify and classify plant diseases. By analyzing images of damaged leaves, stems, and fruits, deep learning models can efficiently detect and locate diseases, thereby assisting farmers in taking timely countermeasures. Early detection of plant diseases is crucial to safeguard crop yields and quality, and reduce the environmental impact of fungicide applications. Until now, most analyses have focused solely on the diagnostic ability of models, thus overlooking the additional potential of providing an explanation supporting the diagnosis. A framework called LIME-BERT has been proposed to improve the interpretability of a state-of-the-art model for predicting crop diseases.

Inclusion of the attention layer plays an important role in providing interpretable insights. This highlights the advantage of multimodal techniques, which can integrate various types of data to offer a comprehensive analysis of plant health. By consolidating different sensory information, multimodal techniques enhance the accuracy and reliability of agricultural disease detection.

7. EVALUATION METRICS

In case of deep learning modeling comparing with a model, both of them are composed of a LSTM network and do not take place information of synthetic pesticides. Past the day on which a sequence prediction model is learned is given, both the risk and the duration of the infested crops sequence in the future and the risk score predict the infestation event afterwards. During the day past revealed that the risk score between the normal state and infested state which spread from low to high in the current crop day. After investing significantly above the threshold risk score, the infestation does increasing in strawberries, tomatoes, and rice as early as the days.

Nowadays, numerous fruit and vegetable crops are into cultivation in controlled environments such as smart farms, greenhouses, and plant factories. Barn and greenhouse cultivation offers big advantages in that growing conditions and influences pests and disease can controlled comparatively easily compare with regular fields. However, it is tough to cope with the increasing demand for explaining as secure or hydroponically contaminants fruit and vegetable high investment. In order to stably produce high quality produce, breeding, and to acquire monitoring of nutrients and diseases since the grow environment is more highly dependent on man. Reduce those factors the multicenter data of growth environment information of a certain crop is analyzed collected from various growth facility farms. Various tests have been conducted to confirm the experimental results and the test results in different situations.

7.1. Accuracy and Precision

With the evolution of modern agriculture and precision farming, the efficient detection method and accurate detection of crop diseases have become one of the pivotal research areas. In this study, an interpretative high-accuracy and high-precision method for rice disease detection based on the transfer learning is presented. First, this method investigates multiple data types related to crop diseases, including multispectral images, environmental information and meteorological data. The validity of these data sets is confirmed by experimentation. Multisource data can refine the detection results of experts. Second, to further extract the relationship between data attributes and crop diseases, multiple features from image and weather data are used. The feature selection method based on LASSO and Relief algorithms are used to select the spine features for subsequent modeling. Finally, to stabilize detection quality among different regions and light environments, the data collected around the rice image is transformed to adapt to a pre-built model by the transfer learning algorithm. What is more, a deep insight into the trained model is given by visualization, ensemble pruning and LIME to reveal the interpretability of the model [1].

7.2. Recall and F1 Score

The recall is the ratio of correctly predicted positive observations to the all observations in the class. High recall means the classifier returned most of the relevant items. Recall is the important metric for the patients as it will have a strong effect if people started using the model when deployed. A sick patient will want that all instances of the disease get detected because they could go for treatments early to cure this disease. i.e. now the False Negative has more priority. There are highly confident conclusions about improving F1 score, and the good alternatives are tunning the threshold and adjusting class weight. So from precision, the threshold has been shifted to 0.11 [11]. The F1 score is the weighted average of Precision and Recall. Therefore, this score takes both false positives and false negatives into account. It states that powdery mildew disease can be classified with a precision of 1.0. Nevertheless, for finding top priority, it is crucial to consider the recall [9].

7.3. Confusion Matrix Analysis

The ability to perform more elaborate tasks and to emulate more advanced theories has attributable to the advancements that occurred in combination with computers and the proliferation of large datasets in the last decade. With an increase of 80% between 2018 and 2019, the most notable shift occurred in using active machine learning methods to game the data space and automatically blend historic data into innovative datasets.

Smart bandit-based tutoring technologies are increasingly being used to massively minimize the spectra of data required for some newly developed open-source drugs and machine learning technologies. With AI, a CSO breaks through a given horse-screened plant and an experimental embryonal agent at a laboratory in the walled city.

8. RESULTS AND DISCUSSION

Recent change of the farming paradigm has allowed to manage much more sophisticated systems, facilities or infrastructures those involve smart sensors and equipment to better monitoring environment and operation status. Nowadays, farmers can see the field condition and growth status of crops through smart device like a mobile phone, or drones can be flown over a vast field for aerial photography. This allows detecting and preventing crop diseases and pests more quickly before becoming a big problem. With the development of IoT technology, many agricultural support system services are provided that control the smart farm facility and monitor the growth environment over the Internet. This data collection and analysis are based on the concept of “precision agriculture” through the prediction model based on machine learning or statistical model. Since the prediction diagnosis model is effective in advance response to a potentially unhealthy situation and can take preventive measures, research in this area has focused on various issues.

8.1. Model Performance Analysis

With growing food consumption, the world is also seeing an increasing population, which is estimated to reach 9.7 billion by 2050. Meanwhile, urban development for expanding demographic demanded areas and emerging of climate change, driven our world to face new challenges in food security. Thus, the adoption of advanced agricultural technology is necessary to enhance agricultural practices, while ensuring sustainable use of natural resources and protection of environment. On other side, prediction of diseases or plant’s condition at early stage is crucial to prevent and suppress possible disease outbreak with minimum cost. To achieve that purpose, this work proposed a machine learning framework with deep learning technique to predict the risk of infection of crop pests and diseases in a predictive manner, before establishing developed model to fit it into current crop disease domain.

The proposed framework converts the growth environment data of crops into a latent space using a deep autoencoder and then calculates the risk score for the normal-infestation state. The study further presents the prediction of a linear risk score in a latent space where the entirety of the environmental features learned by the crops are presented.

8.2. Comparison with Traditional Methods

Plant diseases are a major constraint for plant health, and high crop losses in the agricultural system are largely related to such types of diseases. Early diagnosis of such diseases is an urgent need for plant pathologists, as it is often difficult to cure infected plants. Some diseases are similar to nutrient disorders, and nutrient supply can accelerate its spread. Sustainable development, therefore, requires accurate and fast identification of diseases and their separation from nutrient deficiency. There are several methods to identify diseases, such as AI models, expert systems, and sensors. Since the development of deep convolutional neural networks, major avenues have been explored in the field of vision: from object classification and detection to semantic and instance segmentation.

8.3. Implications for Farmers

With the widespread improvement and greater affordability of drone technology and advancements in AI algorithms, AI-based predictive modeling could well become an important disease sensing tool, particularly for larger farms and plantations in middle-income countries [6]. AI-driven predictive modeling has the potential to empower individual local farmers around the world by providing early, on-the-spot disease detection.

In terms of location, high resolution satellite imagery combined with machine learning algorithms is the most commonly and effectively used approach for large-scale crop monitoring. AI-driven crop disease models trained on satellite image data have already been demonstrated to work well on numerous crops, leaf diseases, and bacteria-related diseases. Despite matching the satellite imagery's coarse resolution, drone data can already provide very detailed crop and disease information, a feature that improves the overall performance of many AI models, especially those based on feature extraction.

9. FUTURE DIRECTIONS

In contemporary literature, it is observed that existing convolutional neural network (CNN) models are unable to deliver acceptable outcomes in actual real-time scenarios for various purposes. Initial research directions are oriented towards examining the potential of transformers and transfer learning, as endeavors in this area have yielded auspicious results for particular tasks as compared to currently well-established CNN models. Future research could focus on the enrichment and enhancement of a mobile device dataset that includes actual images of harvested crops in the field as they have been acknowledged to be in high-degree demand. Emphasis is also placed on the urgency of mobile devices in everyday life, demonstrating the need for low-level model design. In response to this need, various architectural studies such as MobileNet and EfficientNet have been carried out. In addition to challenges related to data processing, it is encouraged that models based on transformers are articulated and integrated. From this various current suggestion, it highly suggests that the initial spark should be on the exploration and the merging of models based on transformers for the improvement of plant disease detection by artificial intelligence (AI). Crop disease and pest forecasting methods have become necessary to enhance the protective approach and effective herbal medicine at appropriate times. In this study, a deep learning model, called Crop Disease and Pest Prediction (CDP), is built, which predicts the dangers of crop diseases and insects using time-serial spectrum data. To evaluate the efficiency of this, assessments are carried out for rice destruction, with detections of leaf degradation and leaf reduction among the other models. The results show that the Deep Learning CDP model, tested as an area beneath the ROC (AUC) shape reach 0.80, exceeded the performance of the other models examined [4].

9.1. Advancements in AI Technology

AI technology has made rapid progress in recent years, with applications varying from natural language processing to computer vision. The vast amounts of data collected on crops and the environment in smart agriculture require intelligent analysis mechanisms to capture useful information. AI models have been widely employed in predictive modeling to estimate crop diseases and forecast corresponding control solutions. Nevertheless, the black box phenomenon and conceptual gap between AI mechanisms and human reasoning hinder the comprehension and application of predictive modeling results. A few promising advancements have been made to bridge the gap between black-box AI models and human reasoning.

However, unearthing such variables can be a complex task and often necessitates collecting and preparing vast amounts of data, which may explain the comparatively modest uptake of these models. By contrast, AI-powered models generally require minimal domain knowledge and can directly consume raw data, thereby offering a powerful alternative for tackling such problems [1]. In recent years, researchers and companies have begun to deploy these models to identify and classify plant diseases.

9.2. Integration with IoT and Sensors
An Internet of Things (IoT) network based on the collaboration of multiple intelligent agricultural models and AI technology is presented, potentially capable of connecting plant disease warning networks and solving technology constraints related to collecting, transmitting, and analyzing numerous and frequent disease warning symptoms through the IoT network. A sensor network is established based on IoT and parameters of plant leaves and the environment, and a spam message detection method and a plant disease recognition method are developed based on text information contained in message notifications received by mobile IoT devices. These developments are crucial for making IoT networks intelligent, allowing the automatic recognition, warning and processing of plant diseases through IoT networks. An IoT network will intelligently recognize warning symptoms of plant diseases in a timely manner and automatically send an alarm message notification to farmers for follow-up processing through the IoT network. Farmers are supported in receiving and processing plant disease warning symptom messages to ensure the early diagnosis and appropriate handling of diseased plants.

9.3. Potential for Global Applications
Artificial Intelligence-driven predictive modeling for crop disease detection is a critical application domain, as nearly 25-35% of global food production is lost due to plant diseases. Agro-based economies are specifically vulnerable to such losses. As a step toward building an AI-driven disease detection model for potato and tomato crops, a dataset consisting of time-series environmental and plant health-related information is provided.

Using this dataset and stream-based learning, a state-of-the-art predictive modeling method is proposed that is based on a Convolutional Long Short Term Memory (ConvLSTM) architecture that leverages a powerful combination of convolutional and recurrent layers to improve additional depth and complex modeling over these datasets.

10.CONCLUSION
Recently, the popularity and acceptability of deep-learning methods have surged rapidly, making them ring better at many original tasks requiring the understanding of image data. The success of deep-learning models is mainly attributed to their many powerful features, such as automatic feature extraction and selection, without any prior reliance on the domain-specific knowledge of a field. To date, the literature on employing deep learning for crop disease detection continues to mount, but research focusing on utilizing various types of data, for the purpose of this task, is infrequent. The majority of research on crop disease detection take pressed images of the leaf as a learn input, but the speed of vegetation can also be reflected in the time sequence data. Recently, many scientists have employed recurrent networks to forecast crop disease. A few models have been developed for the detection of periodic crop disease, but due to the features of the selected data set, such as the small image number and the imbalanced data class, the predict capability of the model is limited. Accurate detection of these three kinds of disease status by deep learning can effectively help the treatment of crop diseases on the whole. In short, a new perspective and way to inspect the disease of agricultural crops that integrates off-the-shelf sensors and state-of-the-art machine learning techniques and methods

are provided here. In further, the focused work is to develop sophisticated protective measures and machine learning methods. In expert tests generally involving agronomy students and agricultural experts, the plant classification model also yielded good performance. To serve a broader study community, existing models will be uploaded.

REFERENCES

J. Li, X. Zhao, H. Xu, L. Zhang et al., "An Interpretable High-Accuracy Method for Rice Disease Detection Based on Multisource Data and Transfer Learning," 2023. ncbi.nlm.nih.gov

J. Vardhan and K. Sai Swetha, "Detection of healthy and diseased crops in drone captured images using Deep Learning," 2023. [PDF]

N. Neranjan Thilakarathne, M. Saifullah Abu Bakar, P. Emerolylariffion Abas, and H. Yassin, "A Cloud Enabled Crop Recommendation Platform for Machine Learning-Driven Precision Farming," 2022. ncbi.nlm.nih.gov

S. Lee and C. Mun Yun, "A deep learning model for predicting risks of crop pests and diseases from sequential environmental data," 2023. ncbi.nlm.nih.gov

A. Yasin and R. Fatima, "On the Image-Based Detection of Tomato and Corn leaves Diseases : An in-depth comparative experiments," 2023. [PDF]

F. Uddin Ahmed, A. Das, and M. Zubair, "A Machine Learning Approach for Crop Yield and Disease Prediction Integrating Soil Nutrition and Weather Factors," 2024. [PDF]

S. Jha, V. Luhach, G. Shanker Gupta, and B. Singh, "Crop Disease Classification using Support Vector Machines with Green Chromatic Coordinate (GCC) and Attention based feature extraction for IoT based Smart Agricultural Applications," 2023. [PDF]

E. Oluwatobi Asani, Y. Phineas Osadeyi, A. A. Adegun, S. Viriri et al., "mPD-APP: a mobile-enabled plant diseases diagnosis application using convolutional neural network toward the attainment of a food secure world," 2023. ncbi.nlm.nih.gov

Y. Zhao, Y. Yang, X. Xu, and C. Sun, "Precision detection of crop diseases based on improved YOLOv5 model," 2023. ncbi.nlm.nih.gov

M. Saberi Anari, "A Hybrid Model for Leaf Diseases Classification Based on the Modified Deep Transfer Learning and Ensemble Approach for Agricultural AIoT-Based Monitoring," 2022. ncbi.nlm.nih.gov

B. Jain and S. Periyasamy, "Grapes disease detection using transfer learning," 2022. [PDF]

D. Akogo, I. Samori, C. Akafia, H. Fiagbor et al., "Localized Data Work as a Precondition for Data-Centric ML: A Case Study of Full Lifecycle Crop Disease Identification in Ghana," 2023. [PDF]