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A Novel Smart Agricultural Management System using Hybrid Convolution-based Deep Learning Model with Multitask Classification

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KEYWORDS

Smart Agricultural Management System; Hybrid Convolution (1D-2D)-based Efficientnet B7; Crop Yield prediction; Plant Disease and Pest Detection; Smart Irrigation

ABSTRACT:

Agriculture is essential to the Indian economy. Landowners, who make up 58% of the population, depend on it to make their livelihoods. Every single day, farmers encounter a variety of pest-related difficulties. It is difficult to diagnose the disease manually using human resources. It has an apparent impact on the agricultural sector. The investigation intended to employ innovative methods to identify insects and disorders in the agriculture field. The Internet of Things (IoT) is adding new dimensions to the intelligent agricultural industry. This allows the individual to gather information from farms in the actual moment and send it to faraway locations for analysis. Automatic illness diagnosis is achievable using sensor information and photographic evidence collected in the field. Furthermore, IoT-based intelligent irrigation management tools can aid in improving water supply efficiency in an accurate agricultural environment. Existing efforts gather images from IoT devices for pest identification and categorization, but their precision isn't good enough. Therefore, in this work, an accurate and effective IoT-based smart agriculture management scheme is introduced. In the beginning, from the IoT sensors, the necessary soil and environmental data, field images, and crop and plant images are garnered. In the first phase, the crop yield prediction stage is performed by employing the soil and environmental data and the crop images. Here, the collected images are given as input to the recommended Hybrid Convolution (1D-2D)-based EfficientnetB7 (HCENetB7) technique for predicting the crop yields. In the second phase, the same technique as HCENetB7 is employed for detecting plant disease and pest detection using plant leaf images and soil and environmental data. Whilst in the last stage, smart irrigation is predicted by utilizing the designed HCENetB7 approach using the soil and environmental data and field images. Finally, the numerical analysis is conducted on the recommended smart agriculture management scheme by comparing it with the conventional techniques to ensure the efficiency of the presented scheme.

Introduction

Smart agricultural management integrates cutting-edge technologies with data-driven solutions to optimize agricultural operations, therefore revolutionizing conventional farming techniques [9]. The agriculture industry must deal with issues including rising temperatures, shortages of water, and a desire to feed more people worldwide in a modern dynamic globe. Innovative solutions to these problems and improvements in farming production, sustainability, and efficiency may be found in smart agricultural management [10]. Precision cultivation is a crucial component of smart agricultural management. It is the application of technology to customize farming methods to particular field circumstances [11]. Farmers are able to accurately monitor and regulate factors like moisture in the ground, level of nutrients, and insect infestations by using equipment like Global Positioning System (GPS), sensors, aircraft, and autonomous machinery. Increased agricultural yields, less of an impact on the environment, and higher resource efficiency are all made possible by this focused strategy [12]. Smart agricultural management relies heavily on data to help farmers make decisions based on current, accurate information. Farmers may obtain valuable insights into crop production, outbreaks of diseases, and economic conditions by gathering and analyzing data from many sources, including satellite images, IoT devices, and weather stations [13]. Farmers are empowered to optimize their operations, reduce risks, and maximize revenue with this data-driven strategy.

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Another important element of smart agricultural management is robotics, which increases operational effectiveness by automating labor-intensive processes [14]. Farmers may save time and money by implementing automated irrigation, being fertilized and gathering systems that guarantee accurate and constant application. In agriculture, the use of robotics and artificial intelligence-powered technology is growing in order to boost output and lessen reliance on laborers. It values durability in order to reduce the negative effects of agricultural methods while maintaining long-term profitability. Smart farming methods include integrated pest control, cover crops, and conservation agriculture in order to enhance the condition of the soil, and the environment, and conserve water [15]. Farmers may lessen the consequences of climate change, preserve natural resources, and strengthen the resilience of the food system by using sustainable practices. In the agricultural community, smart agriculture management also fosters communication and cooperation [16]. Farmers are able to share knowledge, obtain important resources, and keep informed about the market thanks to platforms and applications that promote the exchange of data, best practices, and stay informed about industry developments. This interconnected network fosters innovation, knowledge exchange, and continuous improvement in agricultural practices [17].

The way producers handle their everyday activities has fundamentally changed as a result of the IoT being integrated into smart agriculture management. Real-time data collection and sharing is made possible by IoT technology, which connects various gadgets and detectors to the web [18]. IoT is essential to agriculture since it helps to track and regulate a variety of farming processes. IoT sensors, for instance, may be positioned in fields to gather information on the health of crops, temperatures, and the state of the soil [19]. After that, this data is routed to a central framework for analysis, which yields insightful findings for making choices. Through the use of IoT devices, like as drones and tractors with GPS, farmers can precisely track and oversee their crops. This accuracy makes it possible to apply pesticides, fertilizers, and water in targeted ways, which decreases waste and boosts productivity. Preventive analytics in agriculture, which uses sensor data to forecast crop yields, spot any problems early, and optimize planting dates, is another area where IoT is helpful. IoT-enabled devices may also automate monitoring, pest management, and watering, which streamlines operations and guarantees reliable performance [20]. To maximize and encourage crop development, IoT-enabled irrigation systems, for example, may modify water supply depending on current weather information and soil moisture levels. This automation reduces labor costs and operating expenses while simultaneously increasing production [21].

Deep learning techniques have been applied to a wide range of vision applications. As a result, innovative agricultural methods were created. Deep learning in conjunction with image and sensor technology has been extremely helpful in the upkeep and management of farms by forecasting and assessing the farming crop and outdoor characteristics [22]. The Unmanned Aerial Vehicles (UAV)-mounted detectors provide farmers with data regarding water content, temperature, humidity, development of crops, diseased crops, ripening of fruits, the state of the soil, development of leaves, and several other parameters [23]. Additionally, algorithms for deep learning are employed to assess variables like planting conditions, gathering time, watering duration, and others to boost productivity and improve environmental sustainability [24]. Because it can't be predicted by automated farming systems, certain unanticipated events that occur throughout the crop's growth could decrease the total yield from farming [25]. To address this problem and improve overall crop productivity, a deep learning method combined with a smart agriculture surveillance system is developed, and the following are its contributions.

- To suggest the deep learning-based smart agricultural systems that can analyze large datasets to predict crop yields, disease outbreaks, and optimal planting times. By processing historical data and current environmental factors, it can forecast future agricultural trends with high accuracy. This predictive analytics capability helps farmers make proactive decisions to improve crop productivity and reduce risks.
- To propose the HCENetB7-based smart agricultural system leverages the power of EfficientnetB7 to perform prediction and classification tasks with high accuracy. By utilizing this hybrid convolution approach, the system can capture spatial and temporal

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information simultaneously, enhancing the understanding of complex agricultural patterns. This optimized feature extraction capability enables more accurate analysis of crop health, soil conditions, and environmental factors, leading to improved decision-making for farmers.

- To perform multitask classification process provides a holistic approach to farm management by addressing multiple critical aspects of agriculture in a unified framework. By predicting crop yield, detecting plant diseases and pests, and forecasting smart irrigation simultaneously, the model offers a comprehensive view of the farm's overall health and productivity. This holistic perspective allows farmers to implement integrated management strategies that consider the interplay between crop growth, pest control, and water management.
- To validate the efficiency of the proposed smart agriculture management scheme, a comprehensive numerical analysis is conducted. This analysis involves comparing the recommended system with conventional techniques to ensure the superiority and effectiveness of the presented scheme.

The layout of the designed model is given below. Part 2 provides the literature survey, smart agricultural management system using a hybrid convolution-based deep learning model with multitask classification is shown in Part 3, the development of a hybrid convolution-based deep learning model is shown in Part 4, agricultural multitask classification for a hybrid convolution-based deep learning model is offered in part 5, results and discussions are provided in Part 6, and the conclusion is available in Part 7.

I. LITERATURE SURVEY

A. *Related Works*

In 2020, Boursianis *et al.* [1] have provided a detailed presentation of the components and structure of the AREThOU5A IoT system, a smart watering system. They offered an overview of how the system's IoT module functions. Furthermore, as a backup plan for powering the system's IoT nodes, they integrated the Radio Frequency (RF) power-collecting approach into the previously described IoT system. In order to do this, they created and verified a rectenna device for the purpose of collecting RF spectrum. The developed model performed satisfactorily as an atmospheric sources extractor within a natural environment, according to results from experiments.

In 2024, Morchid *et al.* [2] have proposed an intelligent irrigation system employing cloud computing, integrated technologies, and the IoT to increase nutrition. Real-time monitoring of the weather, moisture content, and the level of water was done by the apparatus. It makes use of detectors that were attached to the ESP32 integrated structure, such as the DHT22, water, and level of water gauges. The ThingSpeak internet and ThingView software were utilized by the entire system to communicate wirelessly with the proprietors of farms. The system incorporated interpolation of linearity for the water level calibration of sensors and automated the pump operation according to inputs from the environment. The suggested strategy was shown to reduce water usage for soil watering by 70%, according to the study.

In 2021, Su *et al.* [3] have encouraged the development and advancement of smart farming and brought about the change of the farming sector. They have done this by applying extensive information to the sector of farming, using the wholesale egg cost in an urban area as the subject of study, and evaluating the variables that affect the oscillations of the egg prices. First, they analyzed the pertinent farming large-scale data, and then they represented the information in order to give it an appropriate scientific foundation. The findings demonstrated that farm large-scale data served a significant role in building smart farming and offered robust data backing for innovations in farming economic administration.

In 2022, Suji *et al.* [4] have created a Wireless Sensor Network (WSN) enabled LoRa-based smart agriculture administration and tracking device for rural regions that will substitute the farming surveillance system's present technology. Despite the need for routers, an encrypted network host might be constructed and connected using a router in order to gather impulses or information from the endpoints and send it via the cloud. Applications for end users might take advantage of the information. LoRa satisfied the connectivity gateway by resolving issues with connection failure and energy-efficient data transfer. The effectiveness of farming methods was increased by this smart farming system.

In 2020, Awan *et al.* [5] have suggested a way to improve living standards as industrialization grows for autonomous structures and cloud-based smart farming. However, there were issues with safety and confidentiality, especially when trying to identify corrupted and illicit nodes. Moreover, a unique trust administration system was suggested. The system computed trust according to pre-established schedules and was event-based, utilizing trust variables. By employing several strategies, it preserved the level of trust between suppliers of cloud services with Base Stations (BS). Several simulations were carried out to assess how well the process defends against possible intrusions. The goal of this research was to provide more productive farms and more hospitable surroundings to encourage people to migrate to cities.

In 2020, Ratnakumari *et al.* [6] have presented the Smart Agriculture Management System (SAMS) aimed to boost crop yield while decreasing resource waste using precise agricultural methods. Applying IoT gadgets, the device maintained monitoring of the soil and its surroundings to ensure optimal crop development. It measured humidity, temperature, and subsoil moisture content using multiple devices and NodeMCU detectors. Producers receive SMS warnings regarding the overall condition of their crops through Wi-Fi and charts displaying the information. The goal of this creative strategy was to increase both the amount and the caliber of farm goods.

In 2022, Siddiquee *et al.* [7] have presented smart agricultural monitoring systems for IoT uses. The developed model was previously used to identify and measure crops from agricultural fields. Color thresholding and color segmentation methods were additionally employed to detect defective veggies. Each algorithm was developed and implemented using a machine learning system called Convolutional Neural Network (CNN). The contrast of classical approaches and CNN was performed in MATLAB to determine the best technique for application in this agriculture surveillance system. Relative to traditional approaches, the CNN was the best technique for this study, outperforming previously created methods with a precision of over 90 percent.

In 2021, Rezk *et al.* [8] have presented an IoT-based smart agriculture framework and an automated learning-based forecasting algorithm for forecasting yields of crops and precipitation. This was critical for farmers as well as agricultural managers in agriculturally impacted countries. Drought forecasting has implications for early detection and reducing the effects on agricultural yield. To forecast productivity in agriculture and flooding, the suggested method integrated an additional methodology for the selection of features and the WPART categorization algorithm. A total of five databases were employed to calculate the technique. The suggested method outperformed current approaches in terms of robustness, accuracy, and precision in identifying and forecasting agricultural yield and drought.

B. *Problem statement*

Smart agricultural management involves using technology like IoT, drones, sensors, and data analytics to enhance farming practices. It helps farmers improve efficiency, sustainability, and decision-making on the farm. However, there are challenges associated with smart agricultural management, such as high costs, data management complexities, technology integration issues, cybersecurity risks, skill gaps, reliability concerns, scalability challenges, regulatory issues, interoperability needs, and environmental impacts. Table 1 provides the features and challenges of the existing smart agricultural management systems, and the section given as follows provides the research gaps.

- ❖ One challenge of existing smart agricultural management systems is the complexity of data management. This challenge can be addressed through the use of deep learning models. Deep learning algorithms can analyze and interpret large volumes of agricultural data more effectively than traditional methods. By employing deep learning models, farmers can gain valuable insights from the data collected by smart devices, leading to improved decision-making, resource allocation, and overall farm efficiency
- ❖ Existing models have difficulty in effectively integrating data from different sources and dimensions for comprehensive analysis. This

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challenge can be tackled by employing hybrid convolution techniques that combine both 1D and 2D convolutions. By leveraging hybrid convolution models, farmers can enhance their decision-making processes by extracting meaningful insights from multidimensional agricultural data.

- ❖ Traditional system has the limited ability to optimize multiple tasks simultaneously. This challenge can be effectively addressed by implementing a multitask approach. By utilizing multitask processes; farmers can enhance the efficiency of their agricultural operations by training a single model to perform multiple related tasks concurrently. This approach can lead to improved resource utilization, better prediction accuracy, and overall enhanced farm management.
- ❖ The current smart agricultural management system lacks standardized data for training and testing models. This challenge can be effectively addressed by utilizing processed manual and benchmark datasets. By incorporating manually curated datasets and benchmark datasets that represent a wide range of agricultural scenarios, farmers can improve the accuracy and generalizability of their models. This approach enables better model performance and more reliable decision-making in smart agricultural management.

Overcoming these challenges requires careful planning, investment, and education to successfully implement smart farming practices. To address this problem and improve overall crop productivity, a deep learning method combined with a smart agriculture surveillance system is developed.

TABLE I. FEATURES AND CHALLENGES OF THE EXISTING SMART AGRICULTURAL MANAGEMENT SYSTEMS

Author [citation]	Methodology	Features	Challenges
Boursianis *et al.* [1]	AREThOU5A	• It improves crop yield prediction accuracy. • It enhances resource efficiency by optimizing water and fertilizer usage.	• It requires significant initial investment in technology. • It may lead to job displacement for traditional agricultural workers.
Morchid *et al.* [2]	Embedded System (ESP32)	• It enables early detection of plant diseases and pests. • It helps in automating tasks like irrigation scheduling and pest control.	• It is highly dependent on data accuracy and quality. • It can be vulnerable to cybersecurity threats.
Su *et al.* [3]	Autoregressive Moving Average Mode (ARIMA)	• It provides real-time monitoring of field conditions. • It facilitates precision agriculture practices.	• It may face resistance from farmers unfamiliar with technology. • It requires continuous updates and maintenance.
Suji *et al.* [4]	LoRa	• It assists in predicting optimal planting times. • It enhances data-driven decision-making for farmers.	• It may lack transparency in decision-making processes. • It could lead to overreliance on technology.
Awan *et al.* [5]	AgriTrust	• It enables personalized crop management strategies. • It increases overall farm	• It may not be accessible to all farmers due to cost barriers. • It raises concerns about data

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		productivity, and reduces operational costs.	privacy and ownership.
Ratnakumari *et al.* [6]	SAMS	• It improves soil health management. • It enhances crop quality through better monitoring.	• It may struggle with interpreting complex environmental factors. • It can be challenging to integrate with existing farm systems.
Siddiquee *et al.* [7]	Color thresholding and color segmentation methods	• It aids in weather forecasting for better planning. • It helps in identifying crop stress factors. • It assists in improving livestock management.	• It may result in reduced human interaction in farming. • It could lead to environmental concerns if not implemented sustainably.
Rezk *et al.* [8]	WPART	• It enhances market analysis and forecasting. • It facilitates integration with other smart technologies for comprehensive farm management.	• It may have limitations in predicting extreme weather events accurately. • It may require specialized technical skills for operation.

II. SMART AGRICULTURAL MANAGEMENT SYSTEM USING HYBRID CONVOLUTION-BASED DEEP LEARNING MODEL WITH MULTITASK CLASSIFICATION

A. *Significance of Smart Agricultural Management System*

Smart agricultural management systems play a vital role in revolutionizing the way farming is done today. These systems leverage cutting-edge technologies such as IoT, artificial intelligence, and data analytics to provide farmers with valuable insights and tools to optimize their agricultural processes. One key aspect is precision farming. By utilizing real-time data and sensor technologies, farmers can make data-driven decisions that enable precise management of resources such as water, fertilizers, and pesticides. It not only enhances crop yields but also minimizes waste, leading to cost savings and environmental sustainability. Furthermore, these systems empower farmers with the capability to remotely monitor and control various aspects of their farms. Through the use of drones, sensors, and automated machinery, farmers can efficiently manage tasks such as irrigation, pest control, and crop monitoring from anywhere at any time. This remote accessibility not only saves time and labor but also improves overall farm management practices. Another aspect of this is their role in promoting sustainability. By integrating sustainable farming practices and technologies, these systems help to reduce the environmental impact of agriculture. They enable farmers to adopt practices that conserve resources, minimize pollution, and enhance soil health, contributing to long-term agricultural sustainability and food security. Moreover, these systems extend to enhancing market competitiveness for farmers. By improving productivity, quality, and efficiency, smart agricultural management systems enable farmers to meet consumer demands, comply with regulations, and adapt to market trends. This competitive edge is crucial for farmers to thrive in a rapidly evolving agricultural landscape.

B. *Proposed Multitask Classification Model for Smart Agriculture*

In the realm of smart agricultural management systems, there exist several challenges that can impede their effectiveness and efficiency. One significant challenge is the integration of various data sources and formats. Agricultural data comes in diverse forms, including sensor data, satellite imagery, weather data, and soil information, making it complex to consolidate and analyze cohesively. This integration challenge can lead to data silos, hindering a holistic view of the farm's operations. Another obstacle is the lack of standardized

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data for model training and evaluation. Inconsistent or incomplete datasets can impact the accuracy and reliability of predictive models, affecting decision-making processes on the farm. Moreover, the quality of data collected from sensors or other devices may vary, leading to noise and inaccuracies in the analysis. Furthermore, scalability poses a challenge for existing smart agricultural models. As farms vary in size and complexity, scaling models to suit different agricultural operations can be a daunting task. Ensuring that models can adapt to the specific needs and constraints of individual farms is crucial for widespread adoption and success. Additionally, the interpretability of models is a key challenge. Understanding how a model arrives at a particular decision or recommendation is essential for farmers to trust and act upon the insights provided. Complex models that lack transparency may deter farmers from fully embracing and utilizing smart agricultural technologies. Addressing these challenges through deep learning models, can enhance the efficacy of smart agricultural management systems and ultimately lead to more sustainable and productive farming practices. So, this work suggested a state-of-the-art deep learning-enabled smart agriculture system to overcome the issues that exist in the recent models. Fig. 1 offers its architectural illustration.

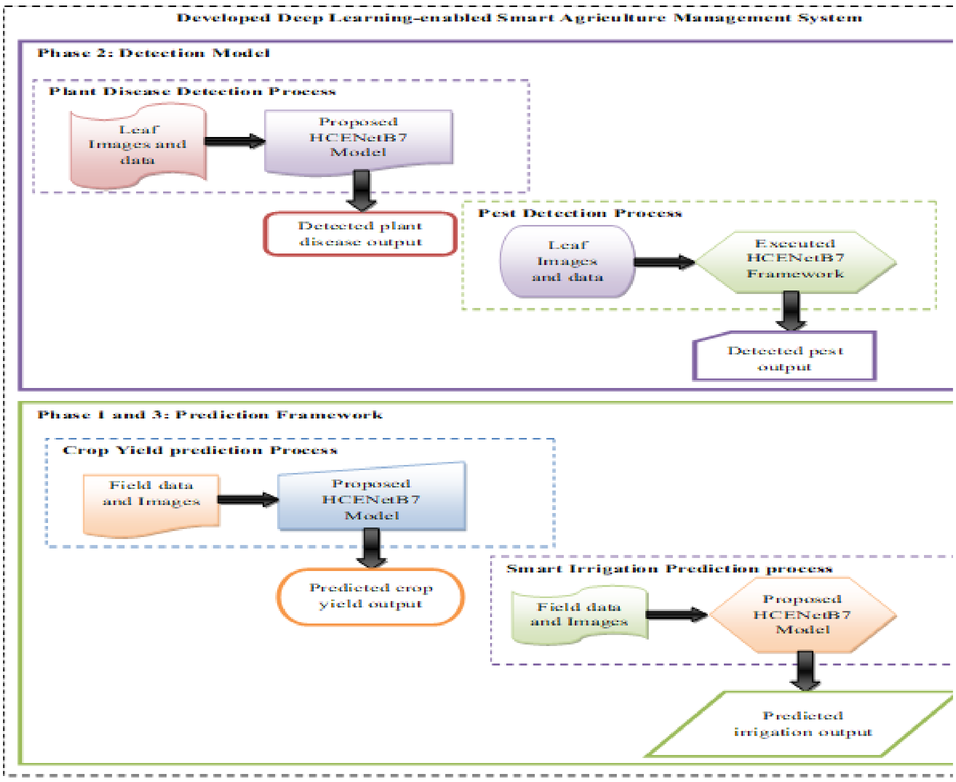

Fig. 1. Architectural Illustration of the Developed Deep Learning enabled Smart Agriculture System

An accurate and effective IoT-based smart agriculture management scheme is introduced in this innovative approach. The developed model aids in increasing crop yield, reducing resource wastage, real-time monitoring of plant health, and improving decision-making for farmers. By leveraging IoT technology and deep learning algorithms, farmers can now optimize their agricultural practices with precision and efficiency. This approach not only enhances productivity but also promotes sustainable farming practices for a greener future. Initially, necessary soil and environmental data, field images, crop, and plant images are gathered from IoT sensors. The system operates in three main phases to optimize crop yield prediction, disease and pest detection, and smart irrigation management.

Phase 1: In the initial phase, the prediction of crop yield involves using the soil, crop images, and

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environmental data gathered. This data is then fed into the HCENetB7 technique, as recommended, to make precise predictions regarding crop yields. The HCENetB7 model plays a crucial role in analyzing the input data and providing accurate insights into the expected crop yields based on the collected soil and environmental information. This process enables farmers to make well-informed decisions about their crops, aiding in effective management and planning for optimal harvest outcomes.

Phase 2: In this phase, the HCENetB7 technique remains instrumental in identifying plant diseases and pests through the analysis of plant and pest images, and data. By applying this technique to examine the images of plant leaves, the system can effectively detect any signs of diseases or pest infestations that might impact crop health and productivity. This approach enables timely intervention to address these issues, safeguarding the crops and ensuring optimal yield outcomes.

Phase 3: In the final stage, the HCENetB7 technique is utilized again for making smart irrigation predictions based on the soil, filed images and environmental data. By employing the HCENetB7 approach to analyze the soil and environmental information, the system can generate accurate forecasts regarding the irrigation needs of the crops. This predictive capability enables farmers to optimize their irrigation practices, ensuring that the crops receive the right amount of water at the right time, leading to improved water efficiency and crop health.

By integrating deep learning techniques with IoT capabilities, this approach aims to enhance agricultural productivity, optimize resource management, and promote sustainable farming practices.

C. *Agricultural Dataset Description*

The description of the collected dataset and images are given subsequently.

Dataset-1 ***("PlantifyDr Dataset")***: The plant and crop images are accumulated via https://www.kaggle.com/datasets/lavaman151/plantifydr-dataset. Access date: 2024-06-17. This collection comprises over 125,000 jpg photographs of ten distinct plant varieties, including (i) apple, (ii) bell pepper, (iii) cherry, (iv) citrus, (v) corn, (vi) grape, (vii) peach, (viii) potato, (ix) strawberry, and (x) tomato. Every plant species includes a file system with sub-folders containing illnesses linked to it. The total quantity of diseases affecting plants equals 37.

Dataset-2 ("***Collection of Different Category of Leaf Images")***: The needed plant and crop images are taken from https://www.kaggle.com/datasets/meetnagadia/collection-of-different-category-of-leaf-images. Access date: 2024-06-17. It contributes to the investigation of plant leaves for proof of identity, identification, and diagnosis of illnesses, among other things. Twelve financially and environmentally advantageous plants, including (i) mango, (ii) arjun, (iii) Alstonia scholaris (iv) lemon, (v) guava, (vi) bael, (vii) jamun, (viii) jatropha, (ix) Pongamia pinnata, (x) basil, (xi) pomegranate, and (xii) chinar, were engaged. Leaf photographs of these species in both normal and exhausted states were collected and distributed across two distinct modules.

Sapota leaf images are collected manually.

Dataset-3 ("***IP102-Dataset***"): The pest images are taken using the link of https://drive.google.com/drive/folders/1svFSy2Da3cVMvekBwe13mzyx38XZ9xWo. Access date: 2024-06-17. This dataset contains 75,222 photographs of pests having the average size of 737 images each class. The size of this dataset is 3.19GB.

Dataset-4 ***("Crop Yield Prediction Dataset")***: The soil and environment data are taken from https://www.kaggle.com/datasets/patelris/crop-yield-prediction-dataset?select=yield.csv. Access date: 2024-06-17. It contains data concerning weather patterns (rain, humidity, etc.), chemicals, and precise crop production which is useful for making judgments regarding agriculture risk mitigation and forecasts for the future.

The collected images and data are indicated by the terms CI_J^{images} and CD_P^{Data} . Fig. 2 offers the collected leaf images.

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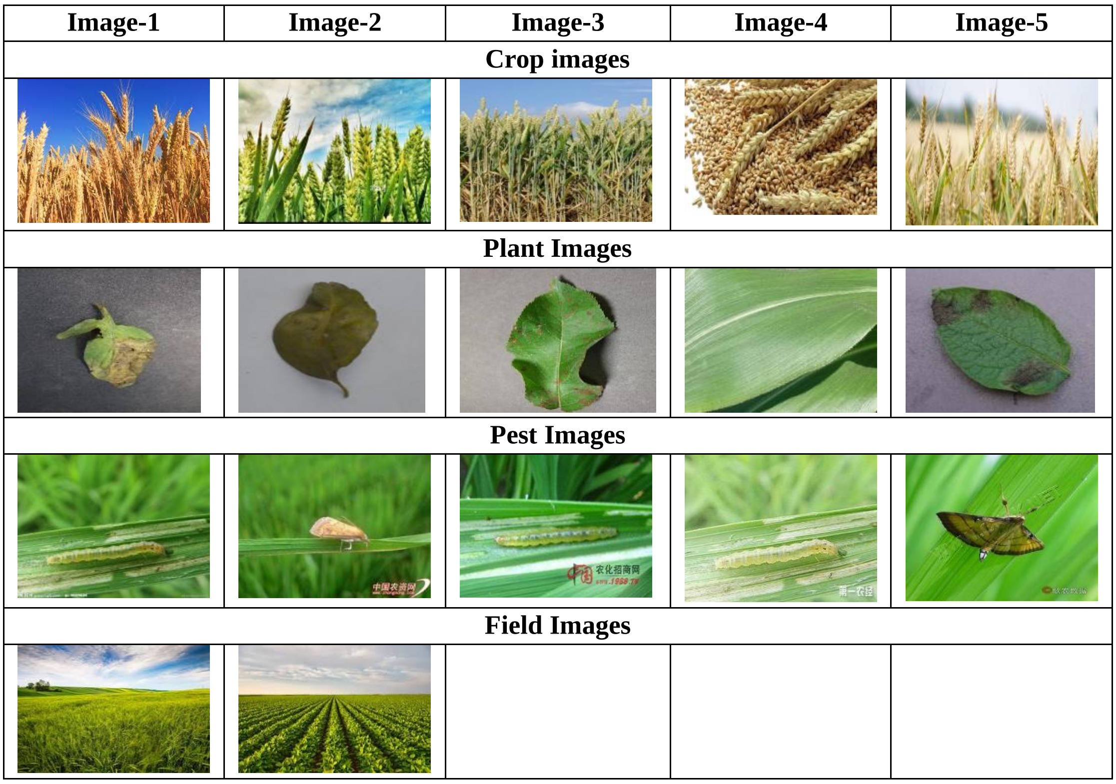

Fig. 2. Collected Sample Images

III. Development of Hybrid Convolution (1D-2D)-Based EfficientNetB7

A. EfficientnetB7

The strong convolutional neural network design is EfficientNetB7 [29] has become well-known because of its effectiveness as well as productivity in the classification of image applications, such as leaf disease identification. EfficientNetB7 may identify illnesses using leaf photographs with solid and trustworthy findings by making effective use of computing power. Increased effectiveness on ImageNet is achieved by modifying specific elements of the previous EfficientNet methodology to create the EfficientNetB7 structure. When compared to different builds with similar ImageNet effectiveness, the EfficientNet is significantly shorter. The very successful combination of expanding algorithms forms the foundation of the EfficientNet topologies. Using the application of this technique, users may modify the ConvNet base to achieve any goal of relatively limited funds, while nonetheless preserving the framework's overall collection transmit rate. Releases from EfficientNet usually outperform comparable algorithms used by CNN like MobileNetV2, AlexNet, and GoogleNet. Editions B0 through B7 of this specific EfficientNet consist of parameters with a range of 5.3M to 66M. Eq. (1) provides an empirical definition of the parameters , and , which stand for breadth, depth, and quality of the image.

(1)

Advanced scalability requires an understanding of maintaining constants for width, resolution, and wide ratio. The grid-based finding approach is used to construct terms including and determine what constitutes 's computational capacity. EfficientNet-B7 consists of 813 steps total, which could be assembled utilizing five distinct components. The first component is the starting point of every subblock and acts as the foundation for the remainder of the subblocks. With the exception of the initial barrier, the second part starts at the initial subblock for every one of all seven crucial challenges. The skipped backlink which joins every subblock is element 3. Element 4 makes it easier to combine each skip backlink into the initial subblock. Element 5 links every sub-block

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against the part that came after it by using a connection that was overlooked. The EfficientNetB7 architecture is an extremely useful instrument as it uses less power, computation expenditures, recall, deductions, and instruction periods when compared with other learning platforms. The combined dimension is matched according to the framework's efficacy to increase the accurateness of the representation. The architecture may be more successful than both VGGNet as well as ResNet methods for scaling if it makes advantage of FLOPS and smaller sizes that vary. The EfficientNetB7 architectural viewpoint is depicted in Fig. 3.

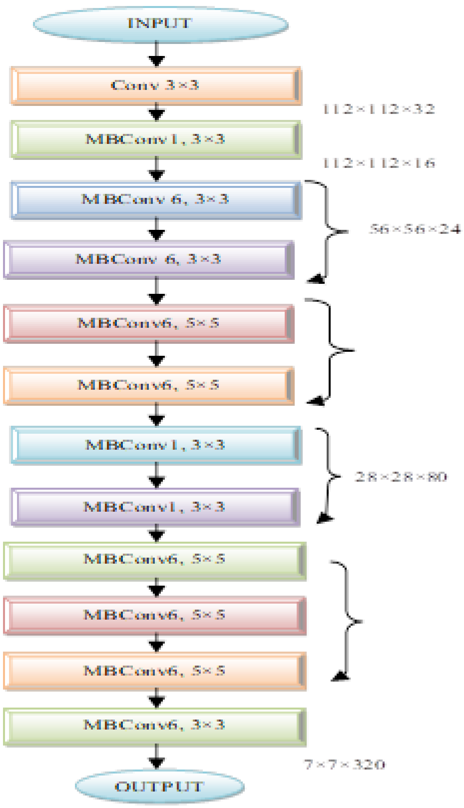

Fig. 3. Architectural Viewpoint of the EfficientNetB7 Model

B. Development of HCENetB7

The collected images and data are given in the developed HCENetB7 model for the effectual crop yield and irrigation prediction, and plant disease and pest detection process. The developed system is a cutting-edge technology that leverages the power of EfficientNetB7 to enhance farming practices through multitask classification. This system integrates hybrid convolutions, combining 1D and 2D features, to efficiently manage multiple agricultural tasks simultaneously, thereby improving productivity and decision-making in the agricultural sector. HCENetB7 plays a crucial role in this system by enabling multitask classification through the analysis of diverse agricultural data. The 1D convolutions focus on processing essential information related to soil quality, environmental variables, and crop characteristics. By utilizing 1D convolutions, the system can accurately classify tasks such as soil health assessment, crop type identification, and monitoring of environmental conditions based on numerical data. In parallel, the 2D convolutions are responsible for analyzing visual data obtained from field images. These convolutions are instrumental in tasks like crop disease detection, growth stage identification, and prediction of irrigation requirements. By incorporating 2D convolutions, the system enhances its ability to classify multiple tasks effectively by extracting visual features from images captured in the agricultural environment. The smart agricultural management system utilizing HCENetB7 offers numerous benefits to farmers and agricultural stakeholders. By harnessing the multitask classification capabilities of HCENetB7, farmers can streamline their operations, optimize resource allocation, and make informed decisions based on data-driven insights. This system empowers farmers to enhance efficiency, sustainability, and profitability in their farming practices by providing a comprehensive analysis of various agricultural parameters. The integration of HCENetB7 represents a significant advancement in precision agriculture. This technology enables farmers to manage multiple tasks efficiently, leading to improved crop management, resource utilization, and overall farm productivity. By utilizing HCENetB7 for multitask classification, the system enables farmers to achieve better outcomes in terms of yield, crop quality, and environmental sustainability. One key advantage of using HCENetB7 in multitask classification is its ability to handle both numerical and visual data simultaneously. The 1D convolutions focus on analyzing numerical data related to soil quality, weather conditions, and crop characteristics, while the 2D convolutions extract visual features from images captured in the field. This dual approach allows for a comprehensive analysis of agricultural parameters, leading to more accurate and

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informed decision-making by farmers and agricultural stakeholders. The structural illustration of the suggested HCENetB7 model is offered in Fig. 4.

Fig. 4. Structural Illustration of the Suggested HCENetB7 Model

IV. AGRICULTURAL MULTITASK CLASSIFICATION FOR HYBRID CONVOLUTION (1D-2D)-BASED EFFICIENTNETB7

A. *Crop Yield Prediction using HCENetB7*

The collected data and images are inputted into the HCENetB7 model for predicting the crop yield. It merges 1D and 2D convolutions to revolutionize crop yield prediction in agriculture. The 1D convolutions in this model focus on analyzing crucial input data related to soil quality, environmental conditions, and other factors influencing crop growth and yield. By processing information such as soil moisture levels, temperature variations, and nutrient content in the soil, the 1D convolutions provide valuable insights into the relationship between soil health, environmental factors, and crop productivity. On the other hand, the integration of 2D convolutions in HCENetB7 allows for the analysis of crop images to assess vital factors like crop growth stages, plant health, and overall vegetation conditions. These visual inputs offer a deeper

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understanding of the spatial distribution of crops, identify areas of stress or potential yield loss, and aid in predicting future crop performance. By combining data from 1D convolutions related to soil and environmental conditions with insights from 2D convolutions derived from crop images, HCENetB7 offers a comprehensive approach to crop yield prediction. Through the power of HCENetB7, farmers and agricultural experts can make informed decisions to optimize crop yield, improve harvest quality, and maximize agricultural productivity. The model's predictive capabilities enable stakeholders to implement targeted interventions, adjust farming practices based on real-time data, and ultimately enhance crop yield outcomes. HCENetB7 represents a significant advancement in precision agriculture, empowering farmers to make data-driven decisions that lead to sustainable and efficient crop production. Finally, the suggested HCENetB7 framework provided the crop yield predicted outcome.

B. Plant Disease and Pest Detection using HCENetB7

The collected data and images are inputted into the HCENetB7 model for detecting plant and pest diseases. This model combines 1D and 2D convolutions to enhance plant disease and pest detection in agriculture. The 1D convolutions in this model are utilized to analyze critical input data related to soil quality, environmental conditions, and other factors impacting plant health. By processing information such as soil pH levels, temperature fluctuations, and humidity, the 1D convolutions provide insights into how soil and environmental factors influence plant susceptibility to diseases and pests. On the other hand, the incorporation of 2D convolutions in HCENetB7 allows for the analysis of images depicting plants and potential pest infestations. These visual inputs enable the model to identify disease symptoms, pest presence, and other abnormalities in plant structures. By leveraging information from 2D convolutions based on plant and pest images, HCENetB7 can accurately detect and classify various plant diseases and pest infestations, aiding in early intervention and effective management strategies. Through the innovative capabilities of HCENetB7, farmers and agricultural experts can proactively monitor plant health, detect diseases and pests at early stages, and implement timely interventions to protect crop yields. The model's ability to integrate insights from both soil-related 1D convolutions and plant image-based 2D convolutions offers a holistic approach to plant health management, empowering stakeholders to make informed decisions and safeguard agricultural productivity. Last, plant and pest-defected outcomes are obtained using the developed HCENetB7.

C. Smart Irrigation Prediction using HCENetB7

The collected data and images inputted into the HCENetB7 model for predicting smart irrigation. In this setup, 1D convolutions are utilized to scrutinize crucial input data concerning soil quality, environmental conditions, and other factors affecting irrigation requirements. By examining information like soil moisture levels, temperature fluctuations, and precipitation patterns, the 1D convolutions provide valuable insights into the soil and environmental conditions necessary for effective irrigation management. Furthermore, the incorporation of 2D convolutions in HCENetB7 enables the analysis of field images to evaluate crop health, growth stages, and water needs. By utilizing visual data from field images, the model can pinpoint areas of water stress, crop growth stages, and overall field conditions that influence irrigation scheduling. The 2D convolutions based on field images empower HCENetB7 to forecast irrigation needs accurately, ensuring efficient water use and crop vitality. Through the advanced functionalities of HCENetB7, farmers and agriculture practitioners can refine their irrigation tactics, optimize water consumption, and enhance crop yield. By amalgamating insights from 1D convolutions related to soil and environmental conditions with details from 2D convolutions based on field images, HCENetB7 provides a holistic solution for smart irrigation prediction, enabling stakeholders to make informed choices based on data for efficient water management in agriculture. HCENetB7 signifies a significant progression in precision agriculture, transforming smart irrigation prediction by leveraging the synergies of 1D and 2D convolutions. Finally, the suggested HCENetB7 system offered the irrigation predicted output.

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V. RESULT AND DISCUSSION

A. Simulation Setup

Python was employed in this work to develop a smart agricultural management system. The performance of the suggested system was compared with existing detection models like Densenet [26], Visual Geometry Group (VGG-19) [27], Resnet-v2 [28], and EfficientnetB7 [29], and the prediction models like Support Vector Machine (SVM) [30], CNN [31], and Long Short-Term Memory (LSTM) [32].

B. Performance Measures

The subsequent section offers the performance metrics.

(a) Mean Absolute Error (MAE) is given in Eq. (2).

(2)

Here, the terms and are the actual and predicted values, is the total data.

(b) Mean Absolute Scaled Error (MASE) is given in Eq. (3).

(3)

(c) Mean Error Percentage (MEP) is given in Eq. (4).

(4)

(d) Root Mean Squared Error (RMSE) is given in Eq. (5).

(5)

(e) Symmetric Mean Absolute Percentage Error (SMAPE) is given in Eq. (6).

(6)

(f) Mean Squared Error (MSE) is given in Eq. (7).

(7)

(g) Normalized Mean Squared Error (NMSE) is given in Eq. (8).

(8)

(h) Mean Absolute Percentage Error (MAPE) is given in Eq. (9).

(9)

(i) Accuracy is given in Eq. (10).

(10)

(j) Balanced Accuracy (BA) is given in Eq. (11).

(11)

(k) False Discovery Rate (FDR) is given in Eq. (12).

(12)

(l) False Negative Rate (FNR) is given in Eq. (13).

(13)

(m) False Omission Rate (FOR) is given in Eq. (14).

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(14)

(n) False Positive Rate (FPR) is given in Eq. (15).

(15)

(o) Specificity is given in Eq. (16).

(16)

(p) Precision is given in Eq. (17).

(17)

(q) Negative Predictive Value (NPV) is given in Eq. (18).

(18)

(r) Positive Likelihood Ratio (PLR) is given in Eq. (19).

(19)

Here, the terms and are the true positive and true negative, and false positive and false negative are defined by the terms and . Moreover, the terms , and are the true positive, sensitivity and true negative rates.

C. Crop Yield Prediction Analysis

Crop yield prediction analysis is given in Fig. 5. This evaluation is performed by varying epochs. It is a crucial component in neural networks and machine learning models, playing a key role in determining the output of each model. When it comes to crop yield prediction analysis, it can enhance the accuracy and efficiency of the predictive models. It helps to introduce non-linearities into the network, allowing it to learn complex patterns and relationships within the data. In the context of crop yield prediction, this non-linearity is essential as crop growth and yield are influenced by various factors that may not have a linear relationship. By using this evaluation, the system can capture these intricate interactions and make more accurate forecasts. Crop yield prediction analysis can help the model learn the threshold values at which certain factors significantly impact crop yield. This can lead to more precise predictions and a better understanding of the underlying dynamics in agricultural systems. This can be valuable in scenarios where factors affecting crop yield may have varying degrees of impact in different directions. By incorporating these epochs into crop yield prediction models, farmers and agricultural stakeholders can benefit from more accurate forecasts, improved decision-making, and optimized resource management. Here, the MAE of the suggested HCENetB78 model is 21.42%, 14.06%, 19.11%, and 8.33% is effective than SVM, CNN, LSTM, and EfficientNet B7 when analyzing the 100^{th} epoch. Thus, the result proved that the use of a developed model enhances the predictive capabilities of the models, enabling them to capture complex relationships and nuances in crop growth dynamics. This, in turn, can lead to more efficient and sustainable agricultural practices, ultimately contributing to increased productivity and food security.

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(a)	(b)
(c)	(d)
(e)	

Fig. 5. Crop Yield Prediction Analysis based on (a) MAE, (b) MASE, (c) MEP, (d) RMSE, and (e) SMAPE

D. Pest Detection Analysis

Pest detection analysis is given in Fig. 6. This evaluation is performed by varying steps per epoch. It is a process that evaluates a model's accuracy and generalization. Through empirical analysis and performance metrics evaluation, researchers can compare the outcomes of pest detection models trained with varying k-fold values. By measuring metrics such as FOR, FNR, BA, and FDR, they can determine the most suitable

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epoch value that optimizes the model's detection capabilities and minimizes false alarms in pest identification. The FDR of the designed HCENetB7 model is 47.82%, 42.85%, 48.71%, and 20% more than DenseNet, VGG-19, ResNet-v2, and EfficientNet at 200th steps per epoch. This shows that the integration of deep learning technologies in agriculture facilitates data-driven decision-making processes for farmers, enabling them to make informed choices based on accurate predictions and streamline farming operations by automating tasks such as crop yield prediction, disease detection, and irrigation scheduling, leading to improved efficiency and productivity.

(a)	(b)
(c)	(d)
(e)	

Fig. 6. Pest Detection Analysis concerning (a) BA, (b) FDR, (c) FNR, (d) FOR, and (e) FPR

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E. *Plant Disease Detection Analysis*

Plant disease detection analysis is given in Fig. 7. This evaluation is performed by varying steps per epoch. An epoch refers to one complete pass of the entire training dataset through the neural network. Varying the number of epochs during training can influence how well the model learns the patterns and features in the data, especially in the context of plant disease classification. By increasing the number of epochs, the model has more opportunities to adjust its weights and biases to minimize the prediction errors. This prolonged exposure to the data can help the model converge to a more optimal solution, potentially improving its ability to classify plant diseases accurately. It helps to find the right balance when determining the number of epochs to prevent overfitting and ensure generalization to new plant disease samples. By varying the number of epochs in plant disease classification analysis, researchers and agricultural experts can fine-tune the model's performance. Through experimentation and validation, they can identify the optimal number of epochs that maximize accuracy without overfitting the model. Moreover, adjusting the epochs allows for a better understanding of how the model learns and adapts to the dataset. Researchers can observe the training progress over different epochs, analyze the loss and accuracy metrics, and make informed decisions on model optimization. The FNR of the proposed HCNetB7 model is 57.98%, 39.02%, 57.26%, and 39.02% more than DenseNet, VGG 19, ResNet v2, and EfficientNet at the 200th steps per epoch. The result proved that the developed system promotes precision farming practices by providing real-time insights into crop health, pest infestations, and irrigation requirements, allowing for targeted interventions.

(a)	(b)
(c)	(d)

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(e)

Fig. 7. Plant Disease Detection Analysis concerning (a) BA, (b) FDR, (c) FNR, (d) FOR, and (e) FPR

F. *Smart Irrigation Prediction Analysis*

Smart irrigation prediction analysis is offered in Fig. 8. This assessment is conducted by different steps per epoch. The step per epochs parameter refers to the number of iterations before updating the model's weights during training. Varying this parameter can impact how quickly the model learns from the data and makes predictions regarding irrigation needs for different crops and soil conditions. By adjusting the step per epoch, researchers and agricultural experts can fine-tune the learning process of the predictive model. A smaller step per epoch value allows for more frequent updates to the model's weights, potentially leading to faster convergence and more precise predictions regarding irrigation requirements. Conversely, a larger step per epoch value means fewer weight updates during training, which can slow down the learning process but may help prevent the model from overfitting to the training data. Finding the optimal balance in setting the step per epoch parameter is crucial to achieving an accurate and efficient smart irrigation prediction system. Through experimentation and validation, researchers can explore different steps per epoch value to observe how the model's performance changes. By analyzing metrics such as prediction accuracy, water usage optimization, and crop yield enhancement, they can determine the most suitable step per epoch setting for their specific smart irrigation application. Furthermore, it allows for a more in-depth understanding of how the model adapts to different learning rates and update frequencies. Researchers can monitor the training progress, evaluate the model's convergence, and make informed decisions on optimizing the smart irrigation prediction system for real-world applications. The NMSE of the proposed system is 45.45%, 32.25%, 39.13%, and 23.63% is greater than SVM, CNN, LSTM, and EfficientNet B7 at the 300th step per epoch. The result proved that the developed system supports sustainable agricultural practices that reduce resource wastage and environmental impact accurately predicting and optimizing irrigation. By automating tasks related to irrigation management, the developed system helps farmers reduce operational costs and optimize resource utilization.

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(a)	(b)
(c)	(d)
(e)	

Fig. 8. Smart Irrigation Prediction Analysis based on (a) Accuracy, (b) MAPE, (c) MSE, (d) NMSE, and (e) One-Norm

G. ROC Analysis on the Developed Model

ROC evaluation is offered in Fig. 9. The ROC assessment is an approach for analyzing the trade-off between an assessment model's true positive outcomes and incorrect positive rates. In the setting of smart agricultural systems, ROC evaluation is useful for assessing the efficacy of forecasting techniques in operations such as crop illness diagnosis, yield prediction, and pest infestation monitoring. One of the primary

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applications of ROC assessment in smart agriculture is to examine the precision and dependability of machine learning methods used in crop disease identification. By studying a ROC curve and computing the Area Under the Curve (AUC) statistic, scientists, as well as farmers, may assess the model's capacity to discern between robust and sick crops, allowing for swift action and preventative measures. Furthermore, ROC analysis is useful in optimizing predictive models for yield prediction in smart agriculture systems. By analyzing the ROC curve and changing the model's parameters, stakeholders may increase the precision of yield projections, resulting in improved processes for making decisions for irrigation, fertilization, and harvesting schedules. In the setting of insect tracking, ROC assessment using smart agricultural systems helps to assess the effectiveness of detection algorithms for properly recognizing and categorizing pest species. Furthermore, ROC evaluation is a useful technique for assessing and choosing the most successful predictive models in smart agriculture uses, guaranteeing consistent and efficient guidance in farming operations. The ROC of the proposed HCNetB7 model is 26.66%, 22.58%, 18.75%, 8.57% more than DenseNet, VGG-19, ResNet v2, EfficientNet B7. Thus, it shows that the developed approach contributes to maximizing crop yields by predicting optimal harvest times, identifying factors affecting yield, and recommending suitable interventions.

(a)	(b)

Fig. 9. ROC evaluation based on (a) Pest Detection, and (b) Plant Disease Detection

H. Performance Analysis on the Suggested Model

Overall performance analysis on the suggested framework based on crop yield prediction, plant disease detection, pest detection, and irrigation prediction is given in Tables II, III, IV, and V. In the realm of smart agriculture systems, overall comparison evaluation allows stakeholders to compare and contrast various agricultural technologies, tools, and methodologies to determine the most suitable and efficient solutions for specific farming needs. This evaluation process involves analyzing multiple factors such as cost-effectiveness, scalability, environmental impact, and overall performance to make informed decisions about technology adoption and implementation. One of the key uses of this is, assessing the impact of different precision agriculture techniques on resource management. By comparing the effectiveness of precision farming technologies such as GPS-guided machinery, drones, and sensor-based monitoring systems, farmers can optimize resource allocation, reduce input wastage, and enhance productivity while minimizing environmental impact. Moreover, it plays a crucial role in evaluating the sustainability and long-term benefits of adopting smart agriculture practices. By comparing traditional farming methods with smart agriculture solutions in terms of water usage, energy consumption, and chemical inputs, farmers and researchers can assess the environmental footprint of different approaches and make informed decisions to promote sustainable agricultural practices. In the context of crop monitoring and management, overall comparison evaluation based on smart agriculture systems helps in evaluating the performance of remote sensing technologies and data analytics tools. By comparing the accuracy, timeliness,

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and cost-effectiveness of different monitoring solutions, farmers can make data-driven decisions to optimize crop health, detect anomalies, and improve overall yield and quality. Furthermore, overall comparison evaluation enables stakeholders in the agricultural sector to assess the scalability and interoperability of smart agriculture technologies. By comparing the compatibility and integration capabilities of different systems, farmers can streamline data management processes, enhance communication between devices, and create a more interconnected and efficient agricultural ecosystem. The NMSE of the suggested HCNetB7 model is 2.45%, 1.39%, 1.93%, and 0.89% enhanced than SVM, CNN, LSTM, and EfficientNet B7 using Table II at 32nd batch size. The result proved that the developed system enables early detection of plant diseases, pest infestations, and irrigation deficiencies, allowing farmers to take timely actions to mitigate risks.

TABLE II. CROP YIELD PREDICTION ANALYSIS

Terms	**SVM [30]**	**CNN [31]**	**LSTM [32]**	**EfficientnetB7 [29]**	**HCENetB7**
			Batch Size-4		
MSE	0.533	0.431	0.479	0.378	0.306
NMSE	0.015	0.012	0.014	0.011	0.009
ONENORM	18033.500	14567.250	16256.500	12769.250	10332.250
MAPE	6.098	4.917	5.522	4.333	3.489
Accuracy	93.902	95.083	94.478	95.667	96.511
			Batch Size-8		
MSE	0.473	0.387	0.436	0.346	0.268
NMSE	0.014	0.011	0.013	0.010	0.008
ONENORM	15989.250	13111.000	14688.750	11711.500	9090.250
MAPE	5.404	4.450	4.952	3.950	3.092
Accuracy	94.596	95.550	95.048	96.050	96.908
			Batch Size-16		
MSE	0.492	0.401	0.445	0.359	0.286
NMSE	0.014	0.012	0.013	0.010	0.008
ONENORM	16622.750	13598.000	15122.250	12114.500	9609.750
MAPE	5.636	4.612	5.141	4.078	3.224
Accuracy	94.364	95.388	94.859	95.922	96.776
			Batch Size-32		
MSE	0.509	0.415	0.463	0.369	0.294
NMSE	0.015	0.012	0.013	0.011	0.008
ONENORM	17279.750	14077.250	15726.750	12455.500	9952.500
MAPE	5.870	4.790	5.340	4.207	3.362
Accuracy	94.130	95.210	94.660	95.793	96.638
			Batch Size-48		
MSE	0.477	0.389	0.430	0.338	0.266
NMSE	0.014	0.011	0.012	0.010	0.008
ONENORM	16015.750	13104.500	14512.500	11470.500	9042.000
MAPE	5.362	4.416	4.901	3.908	3.080
Accuracy	94.638	95.584	95.099	96.092	96.920

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TABLE III. PLANT DISEASE DETECTION ANALYSIS

Terms	Densenet [26]	VGG-19 [27]	Resnet-V2 [28]	EfficientnetB7 [29]	HCENetB7
Batch Size-4					
Accuracy	87.457	89.624	86.317	89.852	91.790
specificity	87.719	89.474	86.404	89.693	91.886
precision	86.761	88.732	85.412	88.967	91.253
NPV	88.106	90.466	87.168	90.687	92.291
PLHR	7.098	8.530	6.342	8.734	11.300
Batch Size-8					
Accuracy	88.369	89.624	87.913	92.474	93.158
specificity	87.939	89.693	87.939	92.544	93.421
precision	87.179	88.915	87.059	91.962	92.874
NPV	89.509	90.287	88.717	92.952	93.421
PLHR	7.365	8.688	7.287	12.392	14.117
Batch Size-16					
Accuracy	85.975	90.308	88.255	90.878	92.816
specificity	86.184	90.132	88.158	90.789	92.982
precision	85.142	89.437	87.324	90.118	92.417
NPV	86.755	91.131	89.135	91.593	93.187
PLHR	6.207	9.171	7.462	9.877	13.201
Batch Size-32					
Accuracy	88.141	89.054	86.545	90.878	92.018
specificity	87.719	89.035	86.623	91.009	91.886
precision	86.946	88.235	85.647	90.307	91.294
NPV	89.286	89.823	87.389	91.410	92.699
PLHR	7.214	8.124	6.463	10.092	11.358
Batch Size-48					
Accuracy	87.229	91.790	89.738	93.273	93.729
specificity	87.500	92.105	89.474	93.202	93.640
precision	86.525	91.449	88.759	92.689	93.160
NPV	87.885	92.105	90.667	93.819	94.260
PLHR	6.955	11.584	8.552	13.731	14.753

TABLE IV. PEST DETECTION ANALYSIS

Terms	Densenet [26]	VGG-19 [27]	Resnet-V2 [28]	EfficientnetB7 [29]	HCENetB7
Batch Size-4					
Accuracy	87.229	87.571	88.255	89.168	91.562
specificity	87.500	87.939	87.939	89.254	91.228
precision	86.525	86.967	87.150	88.443	90.632
NPV	87.885	88.132	89.310	89.845	92.444
PLHR	6.955	7.227	7.346	8.289	10.479
Batch Size-8					
Accuracy	88.141	92.018	89.510	92.132	94.641
specificity	88.377	92.105	89.693	92.105	94.737
precision	87.470	91.489	88.889	91.509	94.313

NPV	88.767	92.511	90.088	92.715	94.945
PLHR	7.562	11.644	8.665	11.674	17.962
Batch Size-16					
Accuracy	88.826	90.536	88.255	92.132	93.615
specificity	88.816	90.789	88.377	91.886	93.421
precision	88.000	90.047	87.500	91.315	92.941
NPV	89.602	90.989	88.962	92.905	94.248
PLHR	7.943	9.800	7.582	11.388	14.261
Batch Size-32					
Accuracy	87.115	89.852	87.571	91.220	91.904
specificity	87.719	89.693	87.500	91.447	91.667
precision	86.667	88.967	86.620	90.758	91.080
NPV	87.527	90.687	88.470	91.648	92.683
PLHR	7.040	8.734	7.012	10.637	11.059
Batch Size-48					
Accuracy	87.799	90.194	89.168	93.158	94.527
specificity	88.158	89.912	89.254	93.202	94.518
precision	87.204	89.227	88.443	92.671	94.090
NPV	88.352	91.111	89.845	93.612	94.934
PLHR	7.381	8.971	8.289	13.696	17.244

TABLE V. SMART IRRIGATION PREDICTION ANALYSIS

Terms	SVM [30]	CNN [31]	LSTM [32]	EfficientnetB7 [29]	HCENetB7
Batch Size-4					
MSE	6.098	4.939	5.527	4.319	3.478
NMSE	0.070	0.056	0.063	0.049	0.040
ONENORM	0.731	0.655	0.692	0.610	0.554
MAPE	34501.552	32008.595	33202.048	30548.667	28640.374
Accuracy	0.318	0.257	0.287	0.223	0.183
Batch Size-8					
MSE	5.407	4.455	4.954	3.933	3.096
NMSE	0.062	0.051	0.057	0.045	0.035
ONENORM	0.686	0.624	0.656	0.581	0.518
MAPE	33087.450	30981.715	31671.315	29658.394	27555.308
Accuracy	0.281	0.232	0.257	0.203	0.161
Batch Size-16					
MSE	5.629	4.620	5.120	4.091	3.229
NMSE	0.064	0.053	0.059	0.047	0.037
ONENORM	0.694	0.635	0.669	0.598	0.531
MAPE	33241.850	31287.791	32241.461	30112.905	28014.293
Accuracy	0.290	0.241	0.267	0.213	0.168
Batch Size-32					
MSE	5.884	4.760	5.342	4.198	3.355
NMSE	0.067	0.054	0.061	0.048	0.038
ONENORM	0.713	0.643	0.685	0.608	0.539

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MAPE	34128.213	31446.107	32819.812	30129.655	28399.764
Accuracy	0.305	0.247	0.280	0.219	0.174
Batch Size-48					
MSE	5.365	4.408	4.898	3.924	3.072
NMSE	0.061	0.050	0.056	0.045	0.035
ONENORM	0.688	0.621	0.656	0.583	0.519
MAPE	32712.424	30493.916	32300.463	29524.975	27567.872
Accuracy	0.281	0.229	0.256	0.203	0.161

VI. CONCLUSION

The developed deep learning-based smart agricultural systems enabled continuous monitoring of crop health parameters, allowing for proactive measures to be taken to prevent disease outbreaks and optimize plant growth. This approach aimed to enhance agricultural productivity, optimize resource management, and promote sustainable farming practices. Initially, the system used IoT sensors to gather soil and environmental data, field images, and crop, and plant images. It operated in three phases: crop yield prediction, disease and pest detection, and smart irrigation management. In the first phase, the HCENetB7 technique was used to predict crop yields using the collected data. This helped farmers to make informed decisions about their crops, aiding in effective management and planning for optimal harvest outcomes. In the second phase, the HCENetB7 technique was used to identify plant diseases and pests through leaf images, enabling timely intervention to protect crops and ensure optimal yield outcomes. In the final phase, the HCENetB7 technique was used for smart irrigation predictions; ensuring farmers receive the right amount of water at the right time, improving water efficiency and crop health. Finally, validations were performed to showcase the effectiveness of the suggested framework. The accuracy of the implemented model was 2.45%, 1.39%, 1.93%, and 0.89% enhanced than SVM, CNN, LSTM, and EfficientNet B7 when the batch size at 8. The result proved, that through the integration of a deep learning model, farmers could enhance crop resilience by proactively addressing disease outbreaks, optimizing irrigation strategies, and maximizing yields, ultimately leading to more sustainable and productive farming practices.

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