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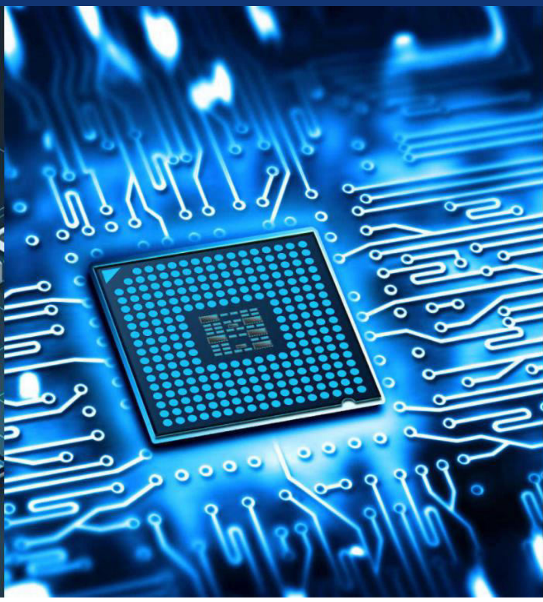

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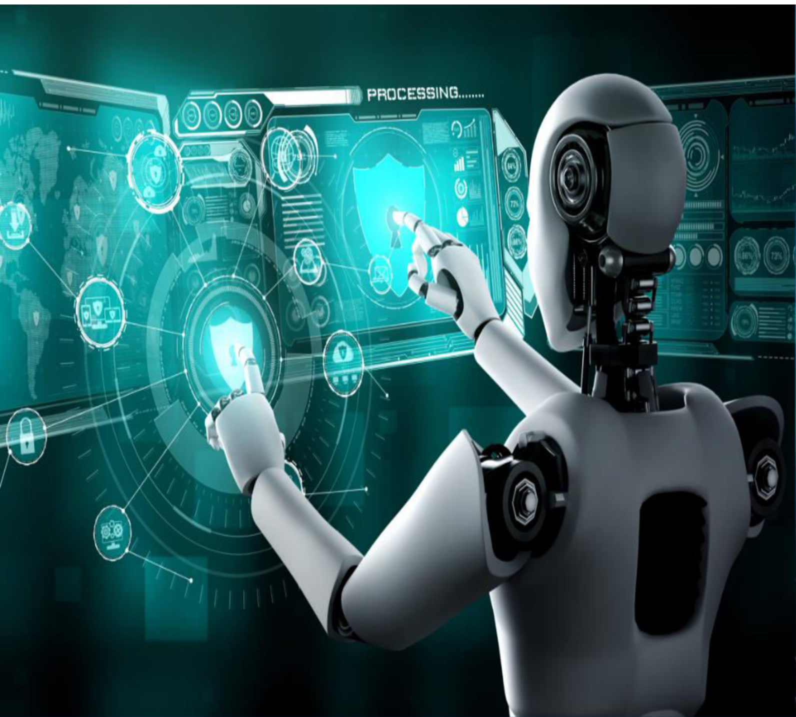

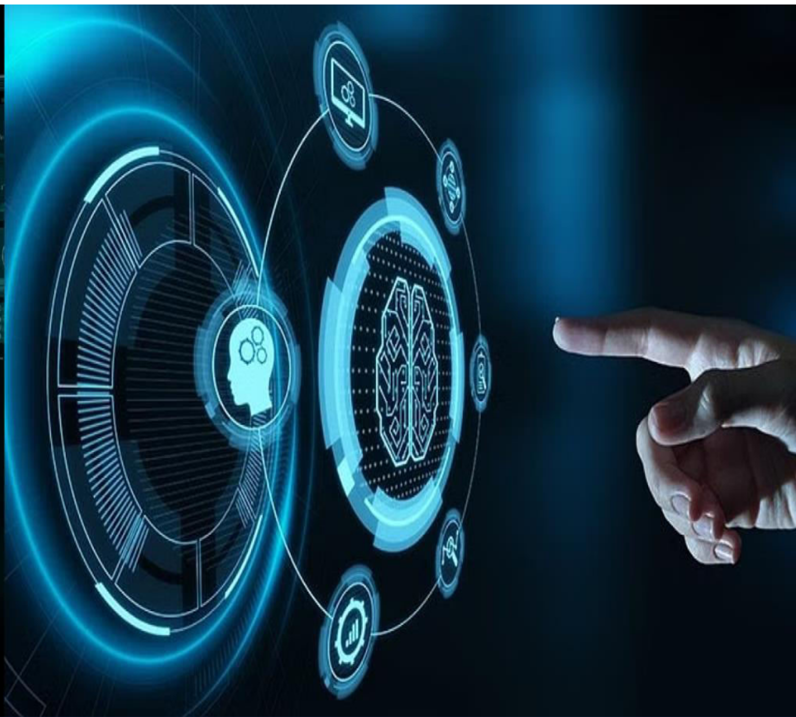

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FarmNet: A Hybrid Deep Learning-Based Multilingual Smart Farming System for Early Crop Disease Detection and Intelligent Decision Support

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ABSTRACT: That crop failures in remote agricultural areas is a big problem in part because those farmers just can't seem to catch issues early enough before its too late. Meanwhile , the automated systems that do exist are so focused on getting results just right that they completely forget about the fact that the real farmers need a few different things from a system – like it to be able to speak their local language, and understand the local weather, and offer some real guidance that actually makes sense to them and is easy to use even for people who have trouble reading .Our team came up with FarmNet as a solution to this mess. FarmNet is basically an intelligent farming system that can tell you right away if any of your plants are sick before its too late-across the whole area its supposed to be working in but our goal with FarmNet went way beyond just making it super accurate-we wanted it to actually help farmers out with some real assistance. So FarmNet can run in lots of different languages, figure out the current weather and give you some super specific guidance that you can actually use – and you can even have a voice assistant .We came up with the idea to use three really powerful deep learning models – ResNet50 and DenseNet121 & EfficientNetB5 – as the core of our system. These models are great at pulling out all the important stuff from images ,which lets us diagnose those plant illnesses early on with pretty good accuracy .But FarmNet is way more than just that – it can even help you look back at past epidemics, get some advice on treatment & product choices through an e-commerce interface and get all the latest info on the local climate in real time. Our system helps farmers make better choices by offering them advide at the right moments when they really need it. We tested FarmNet out and it turned out to be pretty effective – it managed to catch 94.89% of plant diseases. And that not just some number – it shows that we were able to take some of really A1 tech out there and actually use it to solve real problems for farmers in practical ways.

KEYWORDS: Hybrid CNN, Crop Disease Detection, ResNet50,DenseNet121, EfficientNetB5, Deep Learning, Smart Farming System.

I. INTRODUCTION

The agricultural sector functions as the main driving force which sustains the economic system while providing essential nutrition to the rural population. When crops become infected with diseases their productivity decreases which results in financial losses for farmers who face significant risks. The agricultural sector requires immediate crop disease detection methods which scientists have developed for precise and effective disease identification. The system limits damage while producing essential crop growth chemicals which result in complete damage control and improved crop growth results. Experts use traditional crop inspection methods to detect crop diseases through direct field assessments of plant health. Most rural farmers face difficulties accessing experts and modern technology which makes this method of disease identification unfeasible for their use. The population lacks access to modern technology because they experience problems with language understanding digital skills and intrnet access which creates a major gap between available technology znd its practical usage. The field of plant disease detection through computer vision has received new oppurtunities because of advances in deep learning methods. Convolutional Neural Networks (CNNs) have demonstrated remarkable potential for Recognizing visual patterns indicative of crop disease with very high accuracy[5][6][9]. Multiple CNN-based architectures such as ResNet, Inception-ResNet and DenseNet have shown promising results in plant disease identification [1][7][8]. Existing models work to achieve high prediction scores but they fail to deliver vital requirements which include user accessibility and weather-based analysis and effective control methods needed by agricultural workers [4][10].The research introduces FarmNet as a new AI-powered multilingual smart farming system which farmers can use and which operates through three different Convolutional Neural network systems which include ResNet50 and DenseNet121 and EfficientNetB5 to achieve optimal accuracy and real - world utility.

The key contribution of this work are:

- The hybrid CNN model merges ResNet50, DenseNet121, and EfficientNetB5 features to enhance multicrop disease classification accuracy.
- The interface provides multiple languages for users to navigate through its system using icons and local language audio which assists farmers who have limited reading skills.
- The system provides farmers with personalized weather alerts which track weather conditions at their specific farm locations to help them manage climate risks.
- The history feature allows farmers to track previous disease outbreaks which helps them identify recurring problems that support their long-term farm planning decisions.
- The system provides integrated e-commerce recommendations which link each diagnosis to corresponding agricultural products to create an efficient treatment path from problem identification to solution implementation.

II. RELATED WORK

Deep Learning methos that use CNN-based models have achieved successful results in plant disease detection through their hybrid and ensemble systems which beat single model performance by reaching accuracy rates above 94% in their tested datasets [8]. The research community has conducted extensive studies on ResNet and DenseNet and EfficientNet architectures but ResNet provides the best combination of accuracy and fast inference performance which deploys successfully on edge devices with interface times shorter than 200 milliseconds [1][5]. The application of advanced preprocessing techniques which include data augmentation and feature fusion methods and optimization techniques like transfer learning and fine-tuning results in better detection accuracy across multiple crop species and various environmental situations[6][7]. The application of transfer learning techniques to crop disease model training showed 15 to 25 percent performance enhancement over baseline models according to crop disease dataset results [9]. The present systems fail to deliver essential functions because they do not provide multilingual capabilities for users who speak languages other than English and they lack real-time weather data which should support predictive alerts and they need user interfaces which match low-literacy abilities of rural users and they require complete treatment solutions which connect to e-commerce systems and they msut provide enough crop options which develop-region farmers need to succeed in their actual farming practices [2][4]. The existing solutions concrete on achieving detection accuracy while they fail to provide smallholder farmers with usable and practical solutions.

FarmNet addresses these significant gaps through its complete web-based AI decision support system which operated based on four main elements: two disease detection systems and one multilingual support system and one climate warning system and one operational decision support system. The core detection engine uses a hybrid CNN system which combines ResNet50 and DenseNet121 and EfficientNetB5 to merge features from different sources achieving 94.89% accuracy on a diverse crop disease dataset with 94% recall and 95% precision [1][6]. Farmers upload or capture a leaf image through browser interface which provides automated disease diagnosis that achieves 95% confidence together with detailed symptoms, remedies and treated product recommendations which link to treatment protocols [3]. A real-time weather alert module delivers location-aware climate risk information at 6-hour intervals which helps users to make better crop management decisions and the text-to-speech module enables multilingual output in regional languages for better accessibility [4]. A comprehensive history tracking module enables long-term farm management with temporal disease pattern analysis and yield correlation [2]. The system operates as a complete farmer-centric solution which covers all needs from start to finish.

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III. METHODOLOGY

The system uses a hybrid deep learning method which helps farmers by detecting crop diseases through leaf images. The system distributes responsibilities across multiple functional modules which enable each component to execute its specific tasks throughout the complete operational process. The modular design of the system delivers better disease classification results together with easier system usage and enhanced real-world function when compared to traditional single-model detection methods [1][8]. The framework consists of six primary modules that include Image Upload Interface, Hybrid CNN Model, Disease Prediction and Recommendation Module, Weather Alert Module, Text-to-Speech Module, and History Tracking Module. The Image Upload Interface permits farmers to take and submit crop leaf images through their mobile devices or web browsers. The Hybrid CNN Model extracts features from the uploaded image using ResNet50, DenseNet121, and EfficientNetB5 backbones which the system fuses at the feature level to achieve strong disease classification performance [6][8].

The Disease Prediction and Recommendation Module integrates the symptoms, causes, preventive measures, treatment information, and e-commerce product information related to the predicted disease class [3]. The Weather Alert Module retrieves real-time location-based weather information from the internet, which is then used to generate customized disease prediction alerts for the farmer. The Text-to-Speech Module converts the diagnosis results into audio form, making it easier for users who are not literate [4]. The History Tracking Module stores each detection occurrence in MongoDB, allowing for long-term farm management [2].

IV. SYSTEM ARCHITECTURE

The FarmNet framework system architecture has been developed to achieve efficient crop image processing through its system design which enables different intelligent modules to work together. The architecture divides the overall task into distinct functional stages, allowing each module to perform a specific role within the system. The modular system design enables better classification results together with improved system performance and greater accessibility for farming communities with limited resources [1][7].

The architectural design includes six core elements which are depicted in Figure 1. The Web App frontend of FarmNet enables farmers to upload crop images which start their journey through Data Collection and Preprocessing. The system employs augmentation techniques which include five image transformation methods to create standard input quality through its preprocessing stage. The preprocessed image undergoes a Training/Validation Split process which leads to its transfer into the Hybrid CNN Model Training stage [1][7].The Hybrid CNN module uses three pretrained backbones which include ResNet50, DenseNet121, and EfficientNetB5 to extract features through parallel processing. The system combines their outputs in the Feature Fusion Layer which sends data to a Shallow Neural Network Classifier that produces the Disease Prediction and Class Label. The system evaluation process uses standard metrics which include accuracy, precision, recall, F1-score, and loss [5][8].

The prediction system sends its results to two different destinations after completing the classification process. The Text-to-Speech (TTS) module creates native-language audio output from the prediction result. The E-commerce API uses the results to provide product recommendations. The Weather API delivers climate alerts that match specific locations during the entire operational process. The system saves all results and detection events in DynamoDB which enables historical record-keeping and future detection analysis [2][3].

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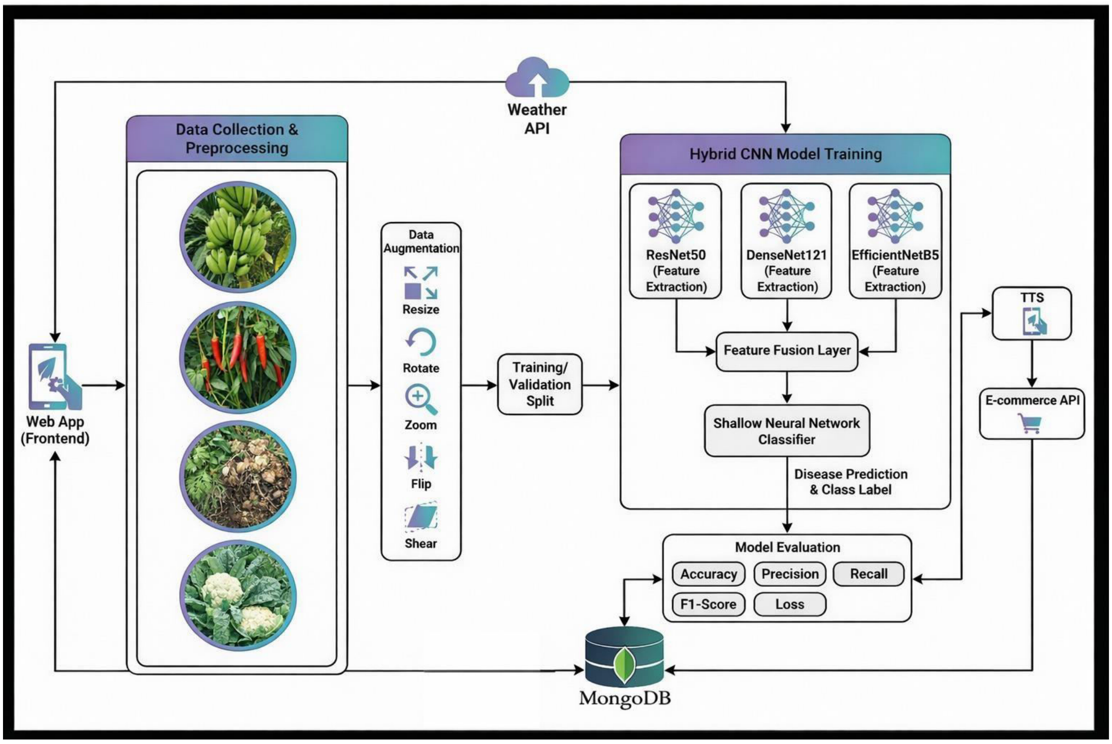

Fig.1. Proposed System Architecture of FarmNet: End-to-End Hybrid CNN Pipeline with Multilingual Support, Weather Integration, and Intelligent Decision Support

V. EVALUATION METRICS AND RESULTS

The FarmNet system underwent deployment and testing on a multi-crop disease database which contained images of banana plants, chilli plants, groundnut plants, radish plants, and cauliflower plants. The system was evaluated using standard classification metrics which included accuracy and precision and recall and F1-score according to evaluation methods used in recent plant disease detection studies[5][8]. **Table I** presents comprehensive metrics for evaluating the proposed hybrid CNN architecture.

Table 1: Hybrid CNN Model Performance: Evaluation Metrics

Metrics	**Macro Avg**	**Weighted Avg**	**Overall Support**
Precision	0.93	0.98	2188
Recall	0.95	0.97	2188
F1-Score	0.94	0.98	2188
Test Accuracy	94.89%	-	-
Validation Accuracy	94.89%	-	-
Training Accuracy	97.35%	-	-
Model Loss	0.18	-	-

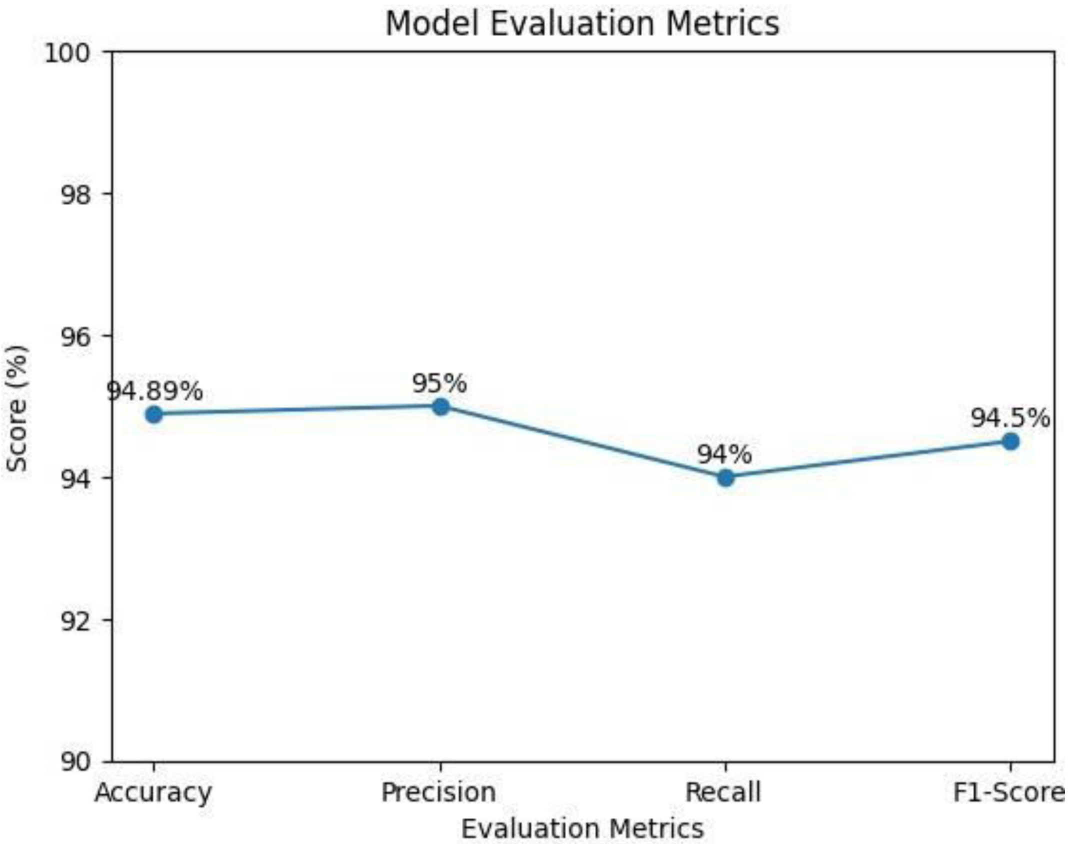

Fig 2: the Model Evaluation metrics of the Hybrid CNN Model

The model achieves an accuracy level of 94.89%, with precision at 95%, recall at 94%, and an F1- Score of 94.5%. This shows that the model is consistent in its performance, with no bias toward false positives or false negatives. This is essential for crop diseases, where false positives or false negatives can affect the results. The model achieves an accuracy level close to 95% while predicting crop diseases. It is also able to recall about 94% of the actual crop diseases. The F1- Score of 94.5% shows that the model is performing well, with an excellent balance between precision and recall. This shows that the model is ready for deployment. The results show that the hybrid CNN architecture, which combines ResNet50, DenseNet121, and EfficientNetB5 using feature fusion, is capable of providing accurate predictions for both tasks. The results show that the model is performing exceptionally well, correctly identifying new crop diseases while aligning with real-world results. This shows that the system is robust, providing farmers with the necessary confidence while making precise decisions during key crop disease intervention.

VI. CONCLUSION AND FUTURE SCOPE

We Developed a hybrid deep learning-based system for smart farming which uses deep learning methods to detect early crop diseases and provide decision-making assistance through their system. The system archieves 94.89% test accuracy using combined deep learning models which use feature fusion to merge the three models ResNet50 and DenseNet121 and EfficientNetB5 [1][5][6][8]. The FarmNet system provides real-world agricultural solutions through its treatment recommendation system and personalized weather update feature [2][3][4]. The system provides users with audio instructions in multiple languages to enhance their understanding of the content. The system supports disease history tracking and e-commerce recommendations which help cross the technological divide between AI systems and agricultural requirements in rural areas [7].

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Future work will concentrate on three main objectives which include expanding the crop disease dataset to test various crops under different environmental conditions and bringing IoT-based sensors into the system for monitoring soil and climate conditions in real-time while researchers work to make models more efficient so they can run on inexpensive mobile devices. The system can be enhanced through two main methods which include advanced explainable AI techniques for model transparency using LIME and SHAP and edge computing offline functionality which enables use in areas with poor internet access and large-scale field testing across multiple agricultural regions to prove system performance under actual conditions. The system will undergo further improvements through three main developments which involve creating predictive yield estimation models which use disease and environmental data, building pest detection system which work with disease detection to create all-inclusive crop health assessment tools, and using federated learning methods to boost system performance while maintaining farmer data confidentiality. The system will develop treatment effectiveness feedback systems which enable farmers to learn from their outcomes while establishing a link between their system and government agricultural subsidy and crop insurance programs and creating cost-benefit analysis tools which will assist farmers in selecting the most economical treatment options. FarmNet will become a complete decision support system which evolves to meet developing-region agricultural needs through ongoing development of regional language models and dialect recognition technology and climate change impact modeling which supports long-term sustainability planning for agricultural operations.

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