Smart Agriculture: Satellite Image-Based Crop Recommendation using CNN and Efficient Net

Anitha Ponraj [1,*]
Associate Professor,
Department of Computer Science and Engineering,
Kalasalingam Academy of Research and Education,
Kalasalingam University,
Virudhnagar, Tamil Nadu, India
anisainotech@gmail.com

PADALA DURGA PRASADU [2]
Dept of Computer Science and Engineering
Kalasalingam Academy of Research and Education
Virudhnagar, Tamil Nadu, India
padalaprasad94@gmail.com

PEETA ANJANA SREE [3]
Dept of Computer Science and Engineering
Kalasalingam Academy of Research and Education
Virudhnagar, Tamil Nadu, India
peetaanjana1504@gmail.com

PETLU LOHITHA LAKSHMI [4]
Dept of Computer Science and Engineering
Kalasalingam Academy of Research and Education
Virudhnagar, Tamil Nadu, India
lohithalakshmipetlu1012@gmail.com

PEYYALA MANIDEEP [5]
Dept of Computer Science and Engineering
Kalasalingam Academy of Research and Education
Virudhnagar, Tamil Nadu, India
manideepyadav380@gmail.com

Lavanya [6]
Assistant Professor,
Department of Computer Science and Engineering,
Kalasalingam Academy of Research and Education,
Kalasalingam University,
Virudhnagar, Tamil Nadu, India
cselavanya1989@gmail.com

***Abstract* - The study introduces a state-of-the-art "soil-based crop recommendation system using Satellite images" that improves farming methods by leveraging Sentinel-2 imagery from several states. Utilizing sophisticated satellite data analysis, the suggested system extracts vital information about soil types and characteristics, allowing for the best crop selection possible for a given set of soil conditions. We use the Swish and Mish activation functions to improve model performance even more. These activations are well-known for their capacity to improve learning dynamics in deep neural networks by speeding up convergence and identifying complex patterns in the data. Our model achieves higher predictive accuracy in crop recommendations based on soil types by utilizing these cutting-edge techniques. This system's primary goal is to increase agricultural productivity and sustainability by offering tailored crop recommendations based on particular soil properties. We provide a data-driven solution that gives farmers practical insights for improving soil management techniques and crop yield optimization across a range of agricultural regions by fusing satellite technology with deep learning methodologies. Our goal is to revolutionize farming practices by empowering stakeholders to make well-informed decisions that improve resource efficiency, boost profitability, and create a more sustainable agricultural ecosystem.**

Key Words – Efficient Net, Deep-learning, Swish Mish Activations, Crop Recommendation, Climate Change, Agriculture, Crops.

I. INTRODUCTION

Historically, manual soil testing, local knowledge, and yield data have served as the foundation for farming practices. Based on their prior experiences and understanding of the land, farmers have used these techniques to choose which crops to plant. However, there are a lot of difficulties with this strategy. In an industry where profit margins are frequently extremely thin, the excessively high margins oferror in soil testing can result in inaccurate assessments. The intricacies of contemporary agriculture, such as shifting soil conditions, climate variations, and changing pest and disease dynamics, are also not sufficiently taken into account by conventional methods. Satellite technology is starting to revolutionize the agricultural industry as a result of these issues. By giving farmers advanced tools to address urgent problems like soil degradation and climate change, it is radically changing the way they select and manage crops. The creation of crop recommendation systems that rely on satellites is one of the most intriguing developments in this field.

Because of its capacity to take high- resolution pictures of the Earth's surface, this satellite has grown to be a vital tool for agricultural management and monitoring. Sentinel-2 provides highly detailed data on environmental factors in future scopes such as soil composition, vegetation health, and moisture levels. This information is crucial for promoting sustainable farming practices, as it reveals land features that conventional methods might miss. By analyzing changes in soil and moisture, farmers can make informed decisions to enhance crop productivity and maintain long-termland health.

i. **Soil composition**: Reveals nutrient levels and deficiencies, crucial for selecting the right crops.

ii. **Vegetation health**: Detects plant stress, diseases, andoverall vitality to improve crop management.

iii. **Land feature detection**: Identifies variations in terrain and soil, which affect crop yields and require targeted strategies.

iv. **Sustainable farming**: By integrating these insights, farming practices can be fine-tuned to minimize resource waste.

To process this rich satellite data, advanced machine learning models like Convolutional Neural Networks (CNNs) are used. Efficient Net, in particular, stands out as an architecture thatoptimizes performance while reducing computational costs. It is highly effective for large-scale data analysis, making it a powerful tool for interpreting Sentinel-2 imagery andrecommending crop management actions.

In addition to improving crop recommendations accuracy, this move to satellite-based data processing empowersfarmers to make better decisions. For instance, farmers can select crops that are more suited to their conditions by using satellite imagery to understand the unique soil properties and field health, which will ultimately increase yield and productivity. Maintaining soil health and advancing long-term sustainability in agriculture depend on improved soil management techniques, which are made possible by this data-driven approach.

Farmers can now make betterdecisions thanks to the shift toward satellite-based data processing, which also enhances the accuracy of crop recommendations. By leveraging satellite imagery, farmers gain a deeper understanding of unique soil properties and field health, enabling them to choose crops better suited to their specific conditions. This approach not only boosts yield and productivitybut also supports the implementation of improved soil management techniques, crucial for maintaining long-term sustainability in agriculture.

a. **Better crop recommendations**: Satellite data helps farmers select crops that match their soil's unique characteristics.

b. **Increased yield**: Understanding soil health and field conditions leads to optimized crop growth and higher productivity.

c. **Soil management**: Data-driven insights encourage the use of sustainable soil practices, preserving long-term soil health.

d. **Field-specific decisions**: Tailored recommendations based on real-time data improve overall farm efficiency.

Additionally, satellite technology provides farmers with the toolsthey need to respond proactively to environmental challenges and changes. As climate change continues to affect agricultural practices worldwide, having real-time access to soil and vegeta tion data allows farmers to adjust their plans to handle new conditions, such as droughts or heavy rainfall. This capability helps ensure resilience and adaptability in farming.

A major advancement has been made agriculture with the use of satellite technology and mach ine learning. With the use of tools like Sentinel-2, farmers can obtain useful information that improves their ability to make decisions. This development helps create a more sustainable agricultural environment that is better prepared to handle future difficulties addition to increasing crop yields and improving farming techniques. This technique has the potential to end agricultural guessing and bring in a new era of scientific accuracy on farms. Farmers have historically made planting selections based on historical facts, local knowledge, and intuit ion. We can encourage cooperation between farmers and researchers democratizing access to advanced analytics and insights obtainedfrom satellite photography.

II. LITERATURE REVIEW

Remote sensing technologies have revolutionized the way modern agriculture is practiced, especially with the advent of satelliteimages. Inoue (2020) highlights the critical role these technologies play in smart farming (SF), enabling more efficient, sustainable and precise crop production by integrating robotics, information and communication technologies, and sensing. (ICT).[1] Satellite- and drone-based remote sensing of crops and soils for smart farming. Recent advances in remote sensing technologies include the deployment of multispectral and hyperspectral sensors on satellites. These systems capture high-resolution data across a range of wavebands, providing detailed information on cropgrowth and soil fertility. The main objective of this paper is to survey the application of machine learning techniques, particularly convolutional neural networks (CNNs), combined with UAV imagery in thefield of precision agriculture. The goal is to improve crop monitoring by solving complex agricultural tasks like crop classification, weed detection, cropland mapping, and field segmentation.

[2] Machine learning and deep learning models integrated with UAVs -acquired images, the aim is to increase productivity, improve yield, and utilize resources effectively. This study concludes by comparing the effectiveness of various machine learning potential benefits for farmers and stakeholders. The research applies advanced deep learning methods using three models—ResNet-50, EfficientNetB2, and MobileNetV2—to classify satellite images into four categories: Cloudy, Desert, Green Area, and Water. These models leverage their unique architectures to enhance the accuracy and efficiency of image classification tasks in remote sensing applications. [3] The images are preprocessed to 256x256 pixels, then split into training and validation sets. The models are trained using theAdam optimizer and evaluated on accuracy and validation met rics to determine their effectiveness in enhancing sustainable decision-making for agriculture, environmental monitoring, and resource management. The study illustrates the benefits and drawbacks of each model for classifying RS images. Efficient NetB2 showed the best generalization, while.

[4] MobileNetV2 faced significant overfitting issues. To develop a robust system that gives accurate crop recommendations by means of deep learning techniques. Theirintention is to refine typical crop selection processes using deepneural networks. It uses different agriculture information, historical crop performance, climate variables and soil conditions through the development of precision agriculture. [5] The proposed system encourages farmers take up more sustainable production types by suggesting crops that make most efficient use of resources and rain with minimum environmental impact.It aims to substantiate its efficacy at farm sites — so that farmers can use state-of-the-art instruments for enhanced production and sustainable agriculture management.

[6] The proposed system suggested is to go over machine learning (ML) in agriculture specifically focusing on disease detection, crop production prediction and soil parameterprediction. IT also includes smart irrigation and livestock production for Machine Learning. This was intended purpose to show off the potential for ML in sustainable agriculture. [7] The aim of the paper is to point out the role soil tests play in modern agriculture for high yield crops and minimum pollutionon the environment. It tries to demonstrate that data-backed crop suggestions using as a parameter the soil attributes, can enhance resource efficiency and sustainable agricultural practices. SharpPhotoelectricity achieves the target of high yield and superior quality, preventing soil erosion and securing food supply. [8] The work has as objective to improve the recognition of crops with spectral and temporal information, for which convolutional neural networks (CNNs) were used combined synthetic imagesthat join different moments and spectral data. The focus is on agricultural monitoring as it will increase productivity,

yield of the crop and utilize resources properly. This method will be concluded with comparison of the potential benefits going to farmers and other commercial stakeholders against present usepractices.

III. PROPOSED METHODOLOGY

A. Data Acquisition

For this project, we downloaded satellite images from the Sentinel Hub using the crops coordinates and Date of Sowing/Planting dates i.e., we used only (Sentinel-2)data to capture India states. With high resolution, multispectral images, Sentinel-2 is exceptional in testing land and soil features. Its purpose was to collect data onthe types of soils in different regions, as it is essential for oursystem that recommends crops. To maintain uniformity and guarantee that the dataset represents a variety of environmental factors such as moisture levels, vegetation health, and surface reflectance our focus was on capturing images that provide snapshots of diverse agricultural landscapes and soil conditions. We selected regions in multiple states as to account for different soil types such as sandy, clay, loam and saline soils.

B. Data preprocessing

Before we can make any analysis on the collectedSentinel-2 satellite imagery, it is being pre-processed for quality and usability. [9] This pre-processing involves steps like atmospheric correction, radiometric calibration, geometric correction and the removal of noise to guaranteethat the data directly indicate any ground situations. Further, the satellite images are georeferenced and image resampling to be integrated seamlessly with other spatial datasets. These are the necessary steps to uphold accuracy and standardization in the data set.

C. Feature Extraction.

Mainly, the system was supposed to mine important properties in Sentinel-2 time series for state forested areas. More specifically, this contribution uses deep learning algorithms, namely a CNN model based on Efficient Net for the spatial analysis of crop dynamics or soil types as well as for the derivation of insights in environmental conditionsover time. [10] To process the satellite images some changes, need to take like noise reduction, geographical structure coordinating, spatial length, vegetation indices, more.

These extracted features give valuable insight into soil health, moisture in the field and conditions of land which is necessary to create crop recommendation. [11] A comparative analysis shows how CNNs perform with respect to other techniques that involve traditional machine learning and recent deep learning models in image processing, particularly when applied to high-dimensional or temporal data. Future directions point toward integrating IoT and cloud platforms for real-time data processing and leveraging large language models for regulatory insights. The features are used as an input to the suggestion generation module,which recommends best suitable crops that grow on specific soil type and environmental conditions. Both the Swish and Mish activation functions support efficient recommendation driven by data to optimize agricultural productivity.

D. Model Training

In this study, we employed the Efficient Net B7 model, the proposed crop recommendation system is built around an advanced deep learning architecture. Efficient Net B7 was chosen for its ability to balance model complexity with computational efficiency, making it highly suitable for large-scale agricultural datasets. By leveraging its scaling capabilities, we ensured that the model could capture intricate relationships between soil properties, climate data, and crop types across different states.

To enhance the model learning capacity, we utilized the Mish activation function instead of traditional activation functions like relu. The Mish function is known for its smooth output, which helps in better gradient flow during training, ultimately improving model convergence and performance. This combination allowed the model to providecrop recommendations for each state with high individual accuracy based on soil, climate, and environmental conditions.

3.1 DataSet

For this project, we collected satellite images from the Sentinel Hub website, specifically utilizing Sentinel-2 satellite data. The dataset focuses on selected regions across various Indian states. The Area of Interest (AOI) was defined for each state to capturerelevant agricultural zones, ensuring that the data aligns with theregions where crop recommendations are needed for this project, we collected satellite images from the Sentinel Hub website, specifically utilizing Sentinel-2 satellite data. The dataset focuseson selected regions across various Indian states.

The Area of Interest (AOI) was defined for each state to capture relevant agricultural zones, ensuring thatthe data aligns with the regions where crop recommendations are needed. To improve the quality of the images, we applied filters to exclude cloud-covered images, ensuring clear satellite data forbetter accuracy in crop prediction. The time range for data collection was carefully chosen to match relevant agricultural seasons, providing a temporal context that enhances the model'spredictive capabilities

3.2 Data Splitting

In In order to assist model training and assessment, the dataset for this study included 1,568 photos in total, which were separated into training and validation sets.

The data was split as follows:

Set for Training: There are 1,255 images total. 80 percent of the entire dataset. The model was trained using this data, which enabled it to recognize the underlying characteristics and patterns in the pictures.

Validation Set: 313 pictures in total 20% of the entire dataset. During training, the model's performance was tracked and its hyperparameters were adjusted using the validation set. By offering an objective assessment of the model, it aids in preventing overfitting. A random seed (seed=123) was specified to ensure the reproducibility of the split, meaning that the same split can be obtained in future runs.

3.3 Model Architecture

A cutting-edge convolutional neural network architecture that has already been trained on the ImageNet dataset is called EfficientNet B7. It was customized and fine-tuned for certain jobs by using a compound scaling approach and removing the top classification layers(include_top=False).

Layers: Layer of Global Average Pooling By reducing the spatial dimensions of the feature maps, the Global Average Pooling Layer effectively summarizes the retrieved features and prepares them for the subsequent layers.

Layer of Dropout: This layer, which is set at 0.5, encourages the model to acquire robust characteristics by randomly discarding half of the neurons during training, preventing overfitting. Dense layer with softmax activation for multi-class classification is the output layer.

The Mish activation function enhances model performance by promoting smoother gradients and improved feature learning in deep neural network. This non-monotonic function allows for more complex representations and effectively addresses issues like the vanishing gradient problem. As a result, Mish is particularly effective in advanced neural architectures, leading to better convergence and overall performance in tasks requiring robust feature extraction.

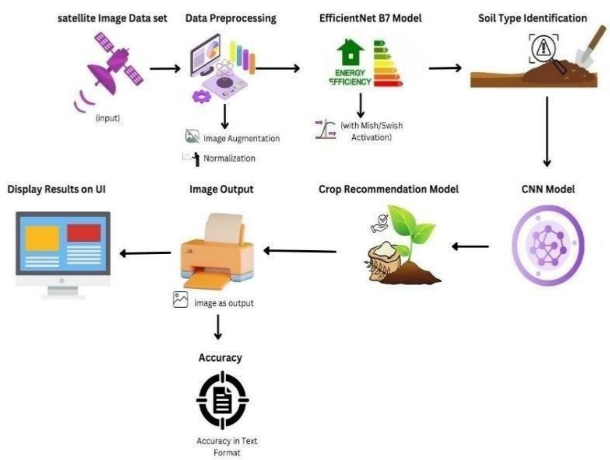

Figure 1. Proposed Smart Agriculture System with Satellite Image Data

Because the model was trained with a batch size of 32, sampleshad to be processed before the internal parameters of the modelwere changed. This method makes learning more efficient by stabilizing the training process through the average of gradients across the batch. Furthermore, the batch size selectionmight affect the memory utilization and training time; smaller sizes enable more frequent updates but may result in noisier gradient estimations. The loss function used to train the model was Sparse Categorical Cross-entropy. This function is ideal when labels are provided for jobs involving multi-class categorization. in full numbers. It minimizes the gap between the predicted real and expected classes by calculating the cross-entropy loss between the predicted probability and the true integer labels in order to effectively manage scenarios when classes are mutually exclusive.

3.4 Model Evaluation

The model evaluation procedure used in this study was carried out utilizing A variety of performance metrics are employed to assess the effectiveness of the crop recommendation system. The first method used was simulated prediction, in which a random crop was chosen as the anticipated crop for each state. This simulates the process of utilizing a machine learning model to make predictions. In order to assess the precision of these forecasts, calculations were made at the state and crop levels.

State-wise accuracy was calculated as the proportion of accurate forecasts for each state, while crop-wise accuracy evaluated the accuracy of predictions for each crop. F1-score, recall, accuracy, and precision were also computed to give more detailed information about the model's performance. Recall recorded the percentage of real crops that were accurately predicted, accuracy calculated the percentage of crops that were properly forecasted out of all projected crops, and the F1-score provided a balance between the two. These indicators aided in assessing the accuracy of forecasts for each crop as well as for the states.

- Precision: Indicates how many of the predicted crops were actually correct.
- Recall: Measures how many actual crops were correctlypredicted.
- F1-Score: Provides a balance between precision and recall, especially useful in cases of imbalanced datasets.

IV. RESULT ANALYSIS & DISCUSSION

The model performed differently for various crops and states. The total number of accurate forecasts divided by the total number of predictions made for each state was used to determine the accuracy for each state. Likewise, crop-wise accuracy was calculated to evaluate the prediction performance of each crop.

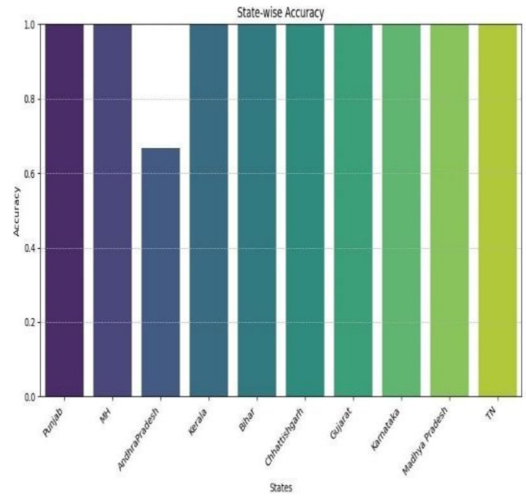

Figure 2. State Wise Accuracy Analysis of Smart Agriculture System with Satellite Image Data

Figure 2 illustrates the accuracy of crop recommendation across various states in India for different crops, showing consistently high performance for the prediction model. Each crop, including maize, paddy, wheat, millet, and others, has achieved an accuracy rate close to 100% across regions like Andhra Pradesh, Gujarat, Karnataka, and Tamil Nadu. This high accuracy level suggests that the model is robust in providing reliable crop recommendations regardless of state, supporting the effectiveness of satellite imagery and machine learning algorithmsin predicting suitable crops for diverse geographical areas. Such precision can enhance decision-making for farmers by aligning crop choices with region-specific conditions, potentially improvingagricultural outcomes.

Precision=TP/TP+FPRecall=TN/TP+FN
F1-Score=2× Precision*Recall /Precision+ Recall

These figures were calculated by tracking true positives (TP), false positives (FP), and false negatives (FN), guaranteeing a thorough examination of the model's capacity for generalization and precise recommendation-making. A deep learning model, like Efficient Net, will take the place of the random prediction mechanism in subsequent rounds. This will enhance these assessment measures and further hone the network's predictive ability.

Figure 3. The satellite images depict crop fields where wheat and rice are cultivated, representing the types of visual data used in

the crop recommendation model. These images can be analyzed for various regions, helping to identify suitable crops based on geographic and climatic features unique to each state. By applying this process to multiple states, the model can consistently assess crop suitability across regions like Andhra Pradesh, Bihar, Gujarat, and others. This uniform approach ensures that each state receives accurate crop recommendations, tailored to its specific agricultural conditions.

Figure 3. State Wise Crop Recommendation of Smart Agriculture System with Satellite Image Data

The crop recommendation model shows perfect accuracy across different crops and states, highlighting its effectiveness and adaptability to local agricultural needs. With precise recommendations—such as maize for Andhra Pradesh and groundnut for Gujarat—it helps farmers make better-informed choices, which could lead to increased productivity.

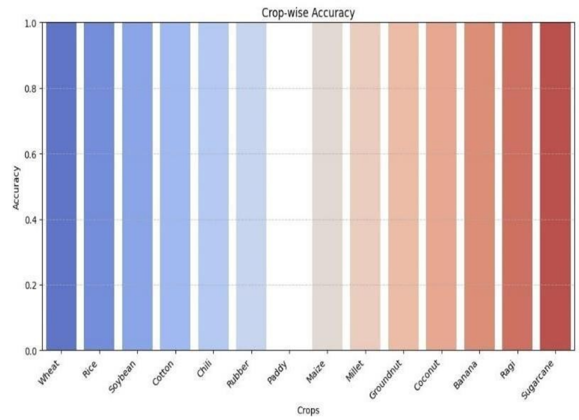

Figure 4. Crop Wise Accuracy Analysis of Smart Agriculture System with Satellite Image Data

The model's consistent performance across various regions also indicates its potential for broader application, making it suitable for larger-scale implementation. But inconsistent performance across classes. Certain states, like Bihar and Punjab, show high recall and precision, suggesting the model has a strong ability to correctly identify instances of these states. However, other states, such as Gujarat and Karnataka, have notably lower F1-scores, indicating difficulty in classifying them accurately.

Figure 5 shows that the classification report and confusion matrix summarize the performance of a model across multiple state-based classes. The model achieves a macro and weighted average F1-score of 0.52, with precision and recall values around 0.55, indicating fair Test accuracy stability suggests that the model performs well over fresh, unexplored data, indicating good generalization. In real deployment, when high accuracy is crucial, the model's capacity to sustain dependable performance across many datasets is demonstrated by the alignment of training and validation accuracy close to test accuracy level.

Classification Report:

	precision	recall	f1-score	support
AndhraPradesh	0.89	0.89	0.89	65
Bihar	0.97	0.97	0.97	148
Chhattishgarh	0.96	0.94	0.95	201
Gujarat	0.88	0.96	0.92	102
Karnataka	0.86	0.92	0.89	135
MH	0.99	0.96	0.98	189
Madhya Pradesh	0.85	0.96	0.90	183
Punjab	1.00	0.99	1.00	163
TN	1.00	0.75	0.86	116
accuracy			0.93	1302
macro avg	0.93	0.93	0.93	1302
weighted avg	0.94	0.93	0.93	1302

Figure 5. Classification Report and Confusion Matrix Summarize the Performance of Proposed Model

The precision, recall, and F1-Score for each state and crop were computed using the formula described. These metrics give a clearer understanding of the prediction quality. High precision indicates few false positives, while high recall suggests the model correctly identifies most actual crops. The F1- score balances these two metrics and is particularly useful in cases where one is much lower than the other.

Figure 6 Shows that Proposed model's accuracy over multiple epochs shows the performance trends of the training, validation, and test sets. Early in the training process, there is a sharp increase in both training and validation accuracy, indicating that the model is learning quickly. However, around the tenth epoch, the rate of improvement slows, and the accuracy stabilizes, suggesting the model is reaching its peak performance. The alignment of training and validation accuracy curves suggests that the model is effectively learning without overfitting. Meanwhile, the test accuracy remains stable at approximately 90%, showing consistent performance on unseen data throughout the training.

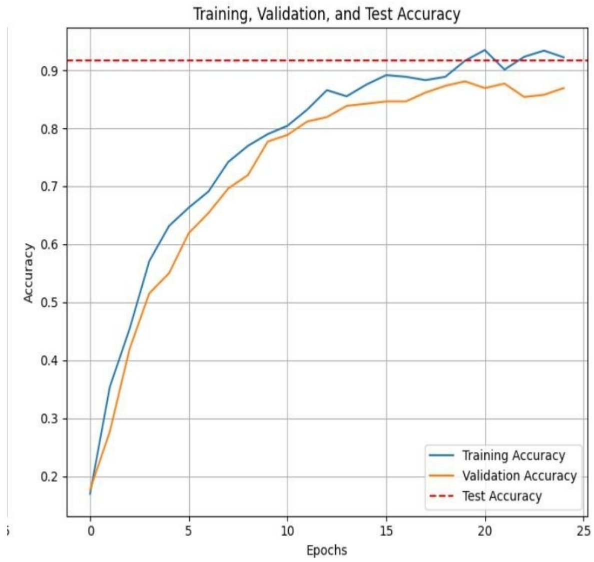

Figure 6. Accuracy Analysis of the Proposed Smart Agriculture System with Satellite Image Data

The classification accuracy for different states and crops based on satellite imagery. The results show varying accuracy across different states, with some regions performing better than others. Crop-wise accuracy highlights the model's ability to predict certain crops more accurately than others. Precision, recall, and F1-score are also calculated for each state and crop, providing insight into the overall prediction quality. These metrics emphasizeareas where the model performs well and where further improvements are needed.

Figure 7 Shows that Proposed model's depicts the evolution of a machine learning model's training, validation, and test loss performance throughout many epochs. The y-axis is a representation of the loss, a statistic that measures how far the actual results depart from the predictions made by the model. The number of epochs—the number of iterations the model goes through during training—is shown on the x-axis. Usually, as training goes on, the loss goes down, indicating that the model is getting better at making predictions. A comparison of training and validation loss aids in evaluating the model's capacity for generalization and possible overfitting.

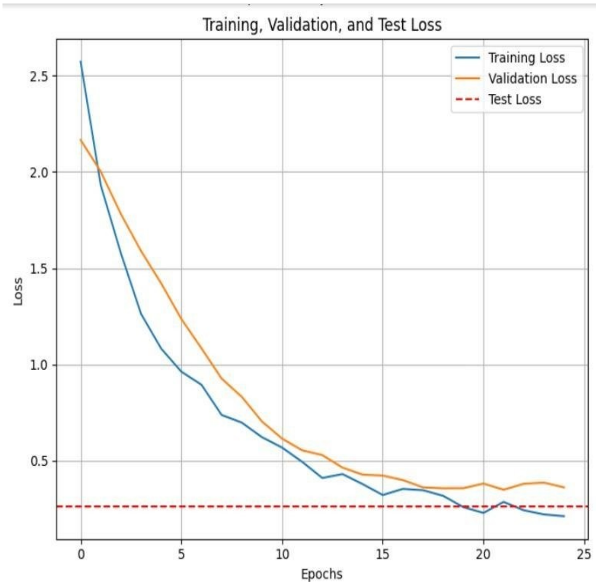

Figure 7. Loss Analysis of the Proposed Smart Agriculture System with Satellite Image Data

As the model recognizes patterns in the data, training and validation losses first drop off quickly, suggesting successful learning. The rate of deterioration slows down after roughly ten epochs, indicating that the model is getting close to performing at its best. The validation loss (orange line) is always greater than the training loss (blue line), however the difference between the two gets smaller as training goes on. Given the validation loss's stability and lack of notable variations, this close alignment points to little overfitting. A low value of test loss, represented by the red dashed line indicates that the model performs well when applied to unknown data. This training, validation, and test loss alignment shows that the model is well-regularized and able to produce accurate predictions in practical situations.

V. CONCLUSION & FUTURE SCOPE

In this research, we developed a crop recommendation system that leverages satellite imagery to enhance agricultural productivity and decision-making for farmers. By employing advanced machine learning techniques, specifically convolutional neural networks (CNNs), the system is designed to analyzesatellite images and accurately predict suitable crops for variousstates in India. This innovative approach not only harnesses thepower of geospatial data but also illustrates the transformative potential of technology in agriculture. As farmers face increase ng challenges such as climate change, resource scarcity, and fluctuating market demands, our system offers a valuable tool to optimize crop selection and promote sustainable farming practices. The evaluation of our model provided important insightsinto its performance, revealing both state-wise and crop-wise accuracy metrics. The results demonstrated that while the model achieved commendable accuracy in certain states, there were notable discrepancies in predicting specific crops. By analyzingprecision, recall, and F1-score. We determined the model's advantages and disadvantages, which is essential to comprehending how reliable it is in practical situations. This thorough evaluation enables us to identify the areas that need more improvement and modification, guaranteeing that the system is strong enough to satisfy the real-world requirements of farmers in a variety of agricultural environments.

Our future work will prioritize improving the model’s accuracy by integrating additional features, such as real-time climate data, soil conditions, and crop rotation practices. Furthermore, we aimto develop a user-friendly application that will make the crop recommendation system accessible to farmers, providing them with actionable insights in a timely manner. By empowering farmers reliable information, the app will facilitate informed decision-making, ultimately leading to more efficient land use, improved crop yields, and enhanced food security.

REFERENCES

1. Medeiros, E., Cruz, J. P., & Silva, M (2024), Ecological Engineering & Environmental Technology, 10(10), 75 – 86. https// doi.org/10.12912/27197050/191244.

2. Clarke, D. E., Stockdale, E. A., Hannam, J. A., Marchant, B. P., & Hallett, S. H. (2024), European Journal of Agronomy, 158, 127224.https// doi.org/10.1016/j.eja.2024.127224

3. Zhang, J., Pan, Y., Wang, W., Shi, Z., Zhang, Z., Fu, Z., Cao, Q., Tian, Y., Zhu, Y., Liu, X., & Cao, W. (2024). Agronomy in Europe, 127, 127132. doi.org/10.1016/j.eja.2024.127132

4. Jin, Z., Shriver, J., Prasad, R., & Zhuang, Q. (2017), 543–560 in Precision Agriculture, 18(5), https://doi.org/10.1007/s11119-016-9488-z

5. Dhande, A., & Malik, R. (2023), AIP Conference Proceedings, 2800, 020126. https// doi.org/10.1063/5.0162893, 2015 IEEE Recent Advances in Intelligent Computational Systems (RAICS) (pp. runners). IEEE. https// doi.org/10.1109/RAICS.2015.7488424

6. Hamuda, E., Mc Ginley, B., Glavin, M., & Jones, E. (2018), Computers and Electronics in Agriculture, 148, 37- 44. https//doi.org/10.1016/j.compag.2018.02.027

7. Abubakar, G. A., Wang, K., Shahtahamssebi, A. R., Xue, X., Belete, M., Gudo, A. J. A., Mohamed Shuka, K. A., & Gan, M. (2020). Sustainability, 12(6), 2539; https://doi.org/10.3390/su12062539.

8. Ponraj, Anitha, and Aroul Canessane. "Radial basis function networks and contrast-limited adaptive histogram equalization filter based early-stage breast cancer detection techniques." *J Comput Sci* 19 (2023): 760-74.

9. Ponraj, Anitha, and R. Aroul Canessane. "Deep learning with histogram of oriented gradients-based computer-aided diagnosis for breast cancer detection and classification." In *2023 3rd International Conference on Smart Data Intelligence (ICSMDI)*, pp. 527-532. IEEE, 2023.

10. Ponraj, Anitha, and R. Aroul Canessane. "Generative adversarial networks with modified wasp swarm algorithm-based early-stage breast cancer detection techniques." *Soft Computing* (2023): 1-13.

11. El Sakka, Mohammad, Mihai Ivanovici, Lotfi Chaari, and Josiane Mothe. 2025. "A Review of CNN Applications in Smart Agriculture Using Multimodal Data" *Sensors* 25, no. 2: 472. https://doi.org/10.3390/s25020472

12. Dhiyanesh, B., Kiruthiga, G., Shakkeera, L., Sharmasth Vali, Y., Asha, A. (2023). Smart IoT Drone-Rover for Sustainable Crop Prediction Based on Mutual Subset Feature Selection Using U-Net CNN for Sustainable Crop Recommendation. In: Karthikeyan, P., Kumar, S., Anbarasu, V. (eds) Drone Data Analytics in Aerial Computing. Transactions on Computer Systems and Networks. Springer, Singapore. https://doi.org/10.1007/978-981-99-5056-0_9