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REMOTE SENSING APPLICATION USING MACHINE LEARNING IN AGRICULTURAL CROP MAPPING

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Abstract - *Remote sensing technology has been widely adopted in the agricultural industry for monitoring crop growth, yield estimation, and identification of plant stress. However, accurately mapping crop types using remote sensing data remains a challenging task. In this project, we propose a novel approach to improve the accuracy of agricultural crop mapping using machine learning techniques. Specifically, we employed convolutional neural network (CNN) frameworks such as MobileNet and VGG19, along with the Python programming language, to achieve high accuracy and low error rates in crop mapping. Our results demonstrate the potential for CNN-based approaches to provide more accurate and reliable crop mapping results compared to existing models. The proposed method has the potential to enhance crop management practices and inform decision-making for farmers and other stakeholders in the agricultural industry.*

Accurate crop mapping is critical for effective agricultural planning and management. In recent years, remote sensing technologies and machine learning algorithms have shown great potential for improving crop mapping accuracy. This study aims to develop a crop mapping model using convolutional neural network (CNN) frameworks such as MobileNetV2 and VGG19. The proposed model is designed to process remote sensing data and identify the different crops present in an agricultural field. The model was trained on a large dataset of remote sensing images and achieved a high accuracy of 97.76% using MobileNetV2. Previous research has explored the use of recurrent neural networks (RNNs) and pre-trained natural language processing models such as BERT for crop mapping.

Additionally, Filter-Embedded Combining Feature Selection has been used to identify relevant features from remote sensing data for improved accuracy. However, the proposed CNN model using MobileNet and VGG19 outperforms these existing models with lower error rates and higher accuracy. This study demonstrates the potential of CNN frameworks in crop mapping using remote sensing data. The proposed model can be used as a reliable tool for agricultural planning and management. Further research can explore the integration of other machine learning algorithms and remote sensing technologies to enhance crop mapping accuracy and efficiency.

***Keywords*:** (Remote Sensing, Crop Mapping, Agriculture, Yield Prediction)

1. INTRODUCTION

For food security and long-term economic viability, accurate and regular monitoring of agricultural health and productivity is essential. The analytics employed while using remote sensing to monitor agriculture must be dependable and precise. Geospatial issues have long been solved with great accuracy thanks to deep learning technologies. However, its use in agricultural applications is still very young and is changing as more study is done. In our model we have used two different architectures of CNN algorithm. They are

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MobileNetV2 and VGG19 and we have compared both architects to give the best accuracy.

An important tool for tracking global agriculture practices is remote sensing images. Earth observation satellites are being launched at a record rate in the "big data" era, giving users access to global imagery with more frequent revisit rates. Deep learning has attracted a lot of attention recently for land-use classification and feature extraction due to its ability to deliver extremely precise results. To ascertain the kinds of issues it may resolve and the situations in which it can be most beneficial, it is crucial to comprehend the nature of machine learning.

The authors of [1] conducted an examination of the use of remote sensing technologies in agriculture, specifically in low- and middle-income countries, highlighting both the advantages and challenges in employing such technologies for crop monitoring, yield prediction, and precision agriculture. In [2], the authors utilized unsupervised data labeling and deep learning techniques to detect weeds in line crops from UAV images, achieving high accuracy. In [3], the use of convolutional neural networks (CNNs) in agriculture was reviewed, including their applications in crop classification, yield estimation, and disease detection. In [4], remote sensing data and a deep learning algorithm called Deep Convolutional Neural Networks were used for land cover and crop type classification, resulting in high accuracy. In [5], Performed a meta-analysis and review of the use of deep learning in remote sensing applications, discussing various deep learning models employed for crop mapping, land cover classification, and object detection. In [6], aerial imagery and deep learning were utilized for scene and environment monitoring, with high accuracy achieved through the use of a deep learning approach called Fully Convolutional Networks. [7] Developed a multiclass weed species image dataset called DeepWeeds, discussing its numerous applications in weed detection and classification through deep learning. Finally, [8] combined various features, including vegetation indices, textural features, and crop phenology, with a decision tree algorithm for object-based crop identification, resulting in high accuracy.

2. REQUIREMENT ANALYSIS

The ENVI Deep Learning module is designed to harness the power of TensorFlow, a convolutional neural network (CNN) framework. CNNs utilize deep neural networks to extract complex features from data in a hierarchical manner. As the model progresses through the layers of data, it learns increasingly sophisticated features, starting with low-level spatial patterns like edges. To illustrate the difference between machine learning and deep learning, a machine learning algorithm can identify different vehicle colors based on pixel values in high-resolution images. In contrast, a deep learning system can recognize various vehicle colors, as well as different shapes and sizes. By incorporating contextual information from neighboring pixels, the algorithm can obtain spatial information. This makes deep learning well-suited to solving spatial problems.

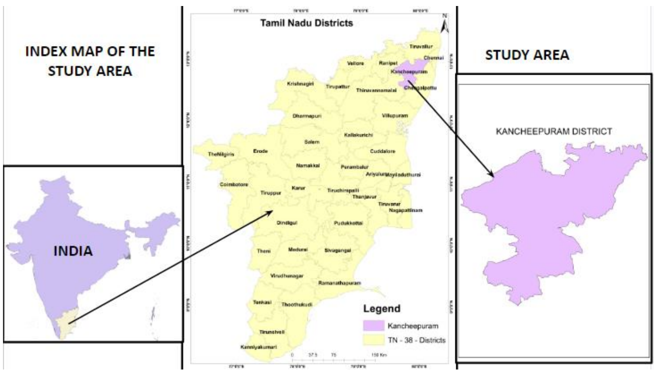

Fig 2.1 - Study Area

2.1 Feasibility Studies/Risk Analysis of the Project

- Downloaded the satellite data in USGS website and IRS from CRSG
- Tiff data format converted into Imagery

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format using ENVI Image processing Software

- Different bands of Satellite Imagery are layer stacked to get the False color Composite Imagery (to get the better interpretation of various themes)
- Taking 4,3,2 band combination for better agricultural studies
- Taking and merging the 4,3,2 band combination for feature extraction
- Satellite data prepared for further processing.

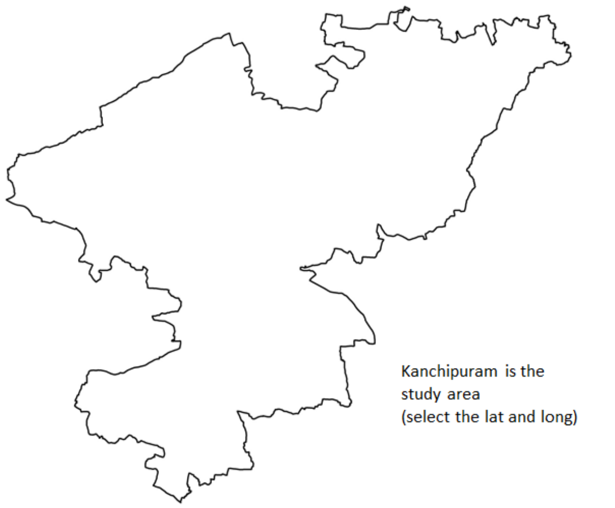

Fig 2.1 - Kanchipuram is the study area (select the latitude and longitude)

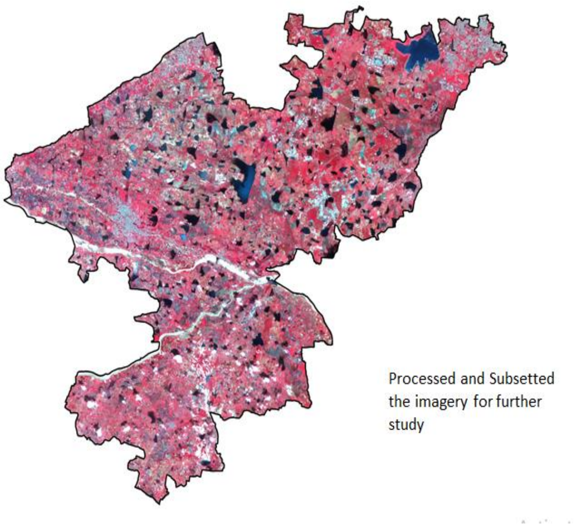

Fig 2.2 - Processed and Subsetted the imagery for further study

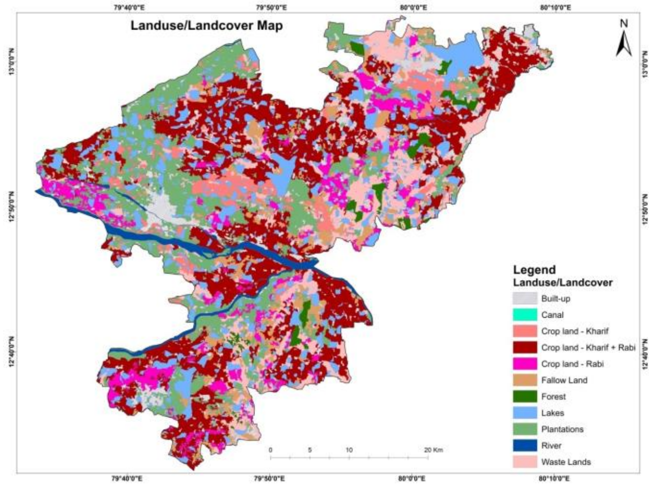

Fig 2.3 - Landuse/Landcover Map

According to the study area, agriculture accounts for the majority of the land use, with double-season crops taking up most of the remaining space.

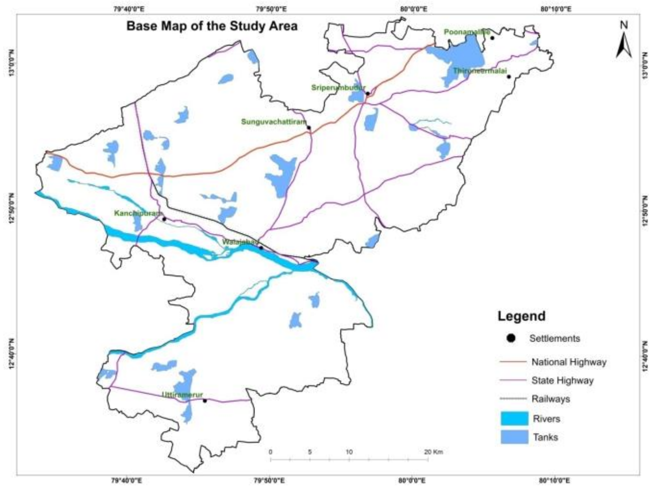

Fig 2.4 - Basemap of Kanchipuram

- Study area Kanchipuram measures roughly 1665 square kilometers.
- It is located between 79° 33' 29.013 and 80° 9' 43.813 degrees east longitude and 12° 31' 50.898 and 13° 2' 48.328 degrees north latitude.
- The district receives a rainfall of 1200 mm
- Palar River is the term to be one of the important perennial river that is the main source of Agriculture and its allied activities.

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Fig 2.5 - Paddy Region - Satellite Image

This is the region we have indexed for the agricultural field of Paddy region from the satellite image.

Fig-2.6 Plantations - Satellite Image

- This is the Satellite image for the main plantations of the study area (Kanchipuram).
- The plantation includes Mango, Banana, watermelon, guava and citrus etc,.

Fig-2.7 True color Composite Satellite Image

- Here the pink color denotes the banana region of the study area
- Blue color denotes the mango region of the study area
- Yellow color denotes the coconut region of the study area

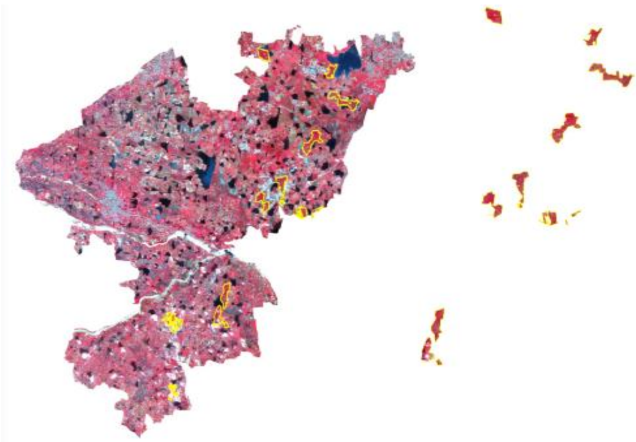

Fig-2.8 Forest region of the study area - Satellite Image

In the Kanchipuram study area, the main types of forests are evergreen, semi-evergreen, and deciduous forests. However, in the specific region under consideration, the predominant forest type is evergreen.

3. EXISTING SYSTEM

There are several existing models in the field of crop mapping that utilize remote sensing data. One approach involves using recurrent neural networks (RNN), specifically long short-term memory (LSTM) models, to process sequential data from remote sensing sensors. This approach is effective because LSTM models can effectively handle sequential data, making them useful for analyzing time-series

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data like that collected from remote sensing sensors. Another approach is to adapt pre-trained natural language processing models, such as BERT, for crop mapping tasks. BERT models are designed to analyze and understand language, but they can also be used to analyze other types of data, including remote sensing data. By adapting BERT models for crop mapping tasks, researchers can leverage the power of pre-trained language models to improve the accuracy of their models.

Additionally, Filter-Embedded Combining Feature Selection (FE-CFS) has been used to identify relevant features from remote sensing data, leading to improved accuracy in crop mapping. FE-CFS is a feature selection method that combines the benefits of both filter and embedded methods. By using FE-CFS, researchers can identify the most important features in remote sensing data, which can then be used to improve the accuracy of crop mapping models.

4. PROPOSED SYSTEM

Satellites are meant to be most useful in the field of agriculture to perform remote sensing. Here we are using satellite images to monitor the crops remotely in a precise manner. Our project involves crop classification from Resource Sat -2 LISS IV Satellite images using CNN (Convolutional Neural Network used for analysis of image) architectures. This model is based on the region of Tamilnadu to focus on different periods. This study focuses on original crop field classifiers with accuracy compared with field verification & validity. Overall, our model's innovative approach demonstrates the potential for the use of CNN frameworks such as MobileNetV2 and VGG19 and Python programming in improving the accuracy and reliability of crop mapping using remote sensing data.

4.1 Selected Methodology Or Process Model

In this multi-step process, five classification techniques are utilized: data collection, data preprocessing, model training, model testing, and prediction. To acquire the necessary dates, Resource Sat 2 LISS IV satellite images are employed, while data preprocessing is accomplished using ENVI and ArcGIS remote sensing software. In instances where training examples are inadequate, the network is trained using data augmentation to develop the required invariance and resilience qualities. The activation layer then generates an output by computing the weighted average of inputs, while pooling layers are utilized to minimize the number of parameters when the images are excessively large, and spatial pooling reduces each map's dimensionality while preserving vital data.

First, the VGG19 model is loaded without its top layer, resulting in a tensor of shape (7, 7, 512) rather than the final classification layer. After that, the base model layers are frozen to prevent training-related modifications, and a custom top layer is added, including a flattened layer, a fully connected dense layer with 512 units and a ReLU activation function, and a final dense layer with 5 units and a softmax activation function. The categorical cross-entropy loss, Adam optimizer, and accuracy are employed as the model is developed. Meanwhile, the top layer of the MobileNetV2 model is excluded to prevent weight updates during training.

The model is trained using the training data and validation data generators for 100 iterations, and the accuracy and loss for each iteration are plotted using Matplotlib. The accuracy is calculated on both the training and validation datasets at the end of each epoch, with classification accuracy representing the ratio of the number of correct predictions to the total number of input samples.

Incorporating a Graphical User Interface (GUI) using PyQt5, this application boasts of an array of interactive controls, including a window, labels, and push buttons. By clicking on the "Upload Image" button, the system triggers the upload image function, enabling the user to select a specific image file through the file dialogue mechanism. Upon

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successful selection, the chosen image file is displayed on the interface using QPixmap. Furthermore, upon clicking the "Predict" button, the application will invoke the predict image function, which subsequently loads and prepares the selected image using load img for further analysis and prediction.

4.2 Architecture Map

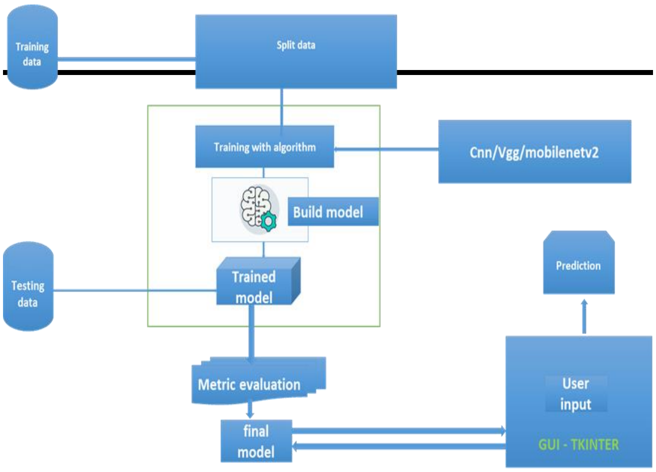

Fig 4.1 Architecture Map

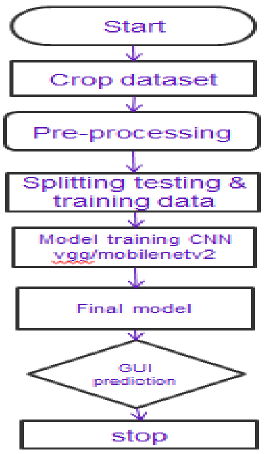

Fig 4.2 - Flow Chart

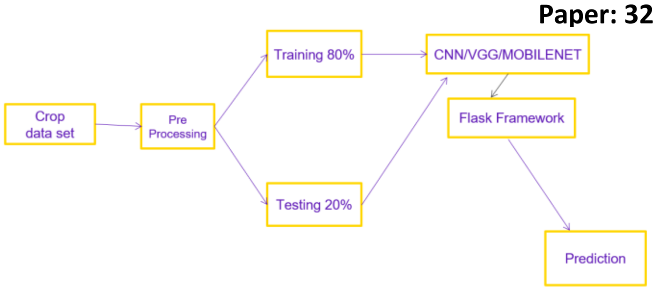

Fig 4.3 DFD Diagram

5. RESULTS

Once the EVI and NDVI values were amalgamated into a cohesive data frame, the information underwent classification based on the NDVI and EVI values' scopes. The sorting process categorized the data into various agricultural classifications, including sugarcane, paddy, mango, coconut, and banana, among others.

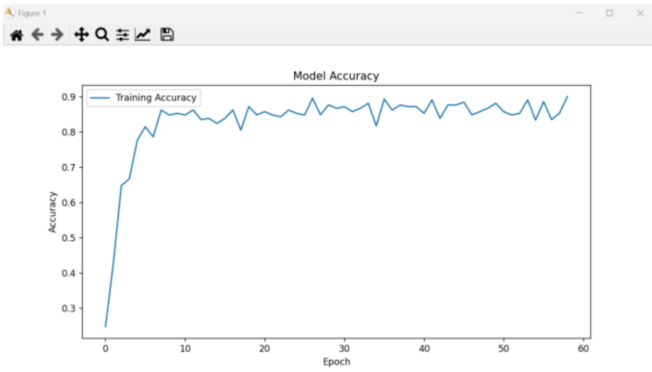

Fig 5.1 Model Accuracy

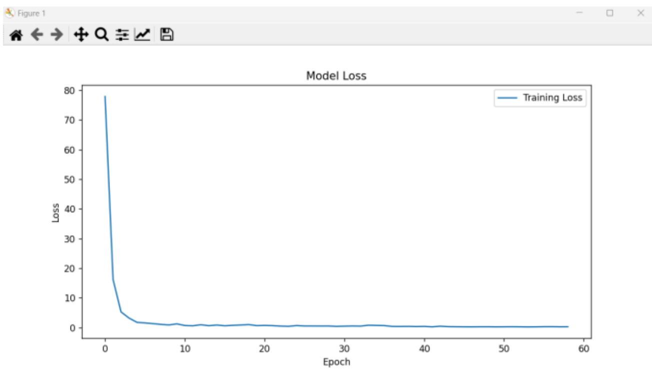

Fig 5.2 Model Loss

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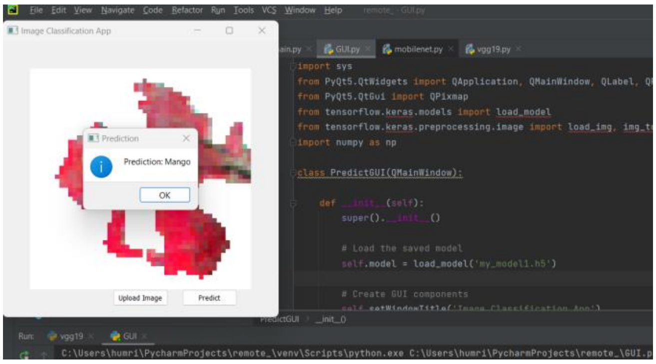

Fig 5.3 Predicted GUI Model

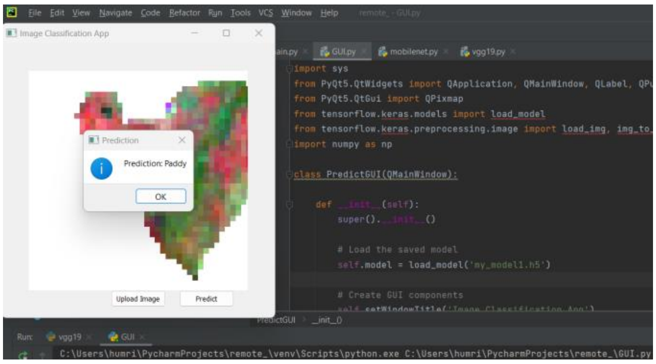

Fig 4.4 Predicted GUI Model

Next, the models were applied to all of the input images, and the accuracy of each model was calculated. The CNN-MobileNetV2 model achieved an accuracy of 97.76%, while the CNN-VGG19 model achieved an accuracy of 87.43%.

6. DISCUSSION AND CONCLUSION

Our methodology aims to reduce the amount of human computation and prediction required for assessing vegetation conditions. Currently, there is a significant amount of discussion regarding the vegetation index and its impact on the overall vegetation condition. Our approach involves the classification of satellite images using ENVI and ArcGIS remote sensing software. By integrating ground data on crop yield (kg/sq km), we can also predict crop production for a future crop season in a particular location.

To improve the accuracy of our forecasts, we also incorporate satellite data in addition to current statistical data. By predicting models for all the collected images, we have achieved a high level of accuracy in our predictions. Our CNN-MobileNetV2 model has a computed accuracy of 97.76, while our CNN-VGG19 model has a computed accuracy of 87.43. Overall, our approach allows for a more efficient and accurate assessment of vegetation conditions and crop production, which can have a significant impact on the agriculture industry.

7. FUTURE WORKS

In order to further improve the accuracy and effectiveness of our machine learning model, several areas of research could be explored. These include:

• Refining the process of collecting field data by focusing on capturing more relevant information at the point of origination that can be used to develop more accurate machine learning models.

• Enhancing the visitation schedule to increase the quantity and quality of data collected for training the model.

• Tweaking the visitation schedule to ensure that the model is trained with more precise and balanced data. This could involve considering factors such as the age of the crops, the specific variety of cane planted, and whether or not there are any crop combinations present in the field. By accounting for these variables, the machine learning model could be better equipped to make accurate predictions about crop yield and other important factors.

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