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A Novel Digital Agriculture: Assessing AI and ML Impact via an iOS Mobile Application

Mr. NAVEEN
Assistant Professor, Department of Computer Science & Engineering, Dronacharya College of Engineering, Gurugram, Haryana
naveen.rathi@ggnindia.dronacharya.info

Mr. HRIDESH GUPTA
Assistant Professor, Department of Computer Science & Engineering, Dronacharya Group of Institutions, Greater Noida, Uttar Pradesh
hridesh.gupta@gnindia.dronacharya.info

Abstract

In the modern era, agriculture plays a crucial role in India's GDP growth. Traditional farming methods are outdated, and farmers are increasingly interested in adopting new technologies. Drones are used for surveillance and pesticide spraying, but they also expose farmers to diseases. Machine Learning (ML) models are used to predict crop diseases, such as Healthy, Boll Rot, and Fungal Leafspot diseases. This research proposes two approaches to prepare the core ML model for cotton disease detection. The first approach uses the CREATEML Mac application with a labelled training and validation dataset, using modified model parameters for better accuracy. The model is trained with a 70:30 ratio of training and validation dataset, predicting diseases with an accuracy of 89%. The second approach uses the TensorFlow framework, using sequential classification type to classify cotton diseases using real field images. Data augmentations with random flip, rotation, and zoom are used to avoid data shortages during training. The model is trained with a 70:30 ratio of training and validation dataset, predicting diseases with an accuracy of 92.5% and 92% respectively. The iOS app is developed with the embedded ML model embedded in it, removing server side dependency and communication time. This research highlights the significant impact of Artificial Intelligence (AI) and ML on agriculture.

Keywords- Artificial Intelligence, Machine learning, IoT, Mobile Applications, Security.

Introduction

AI and ML are increasingly being used in agriculture to improve data analysis and optimization, speed up decision-making, and solve complex problems using complex algorithms. AI can be divided into three categories: supervised learning, unsupervised learning, and reinforcement learning. Supervised learning classifies and processes data using machine language, while unsupervised learning uses unlabelled data without training data. Reinforcement learning is used in gaming to maximize reward in situations without a training dataset[1].

AI systems are used to improve harvest quality and quantity, help farmers determine crop choices, hybrid seed choices, and resource utilization. Traditional manual farming methods require more manpower, money, and time, making automation work with AI & ML in agriculture more efficient and cost-effective [2-6].

In India, agriculture contributes to the GDP around 20%, and increased crop productivity can contribute to GDP. ML-driven image processing allows farmers to recognize weed species, determine crop health, and treat crop diseases. Farmers now rely on AI-enhanced technology

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to meet demand without waste, make smarter harvesting and pricing decisions, identify and automatically remove harmful weeds, and find and treat crop diseases with targeted solutions [3-10].

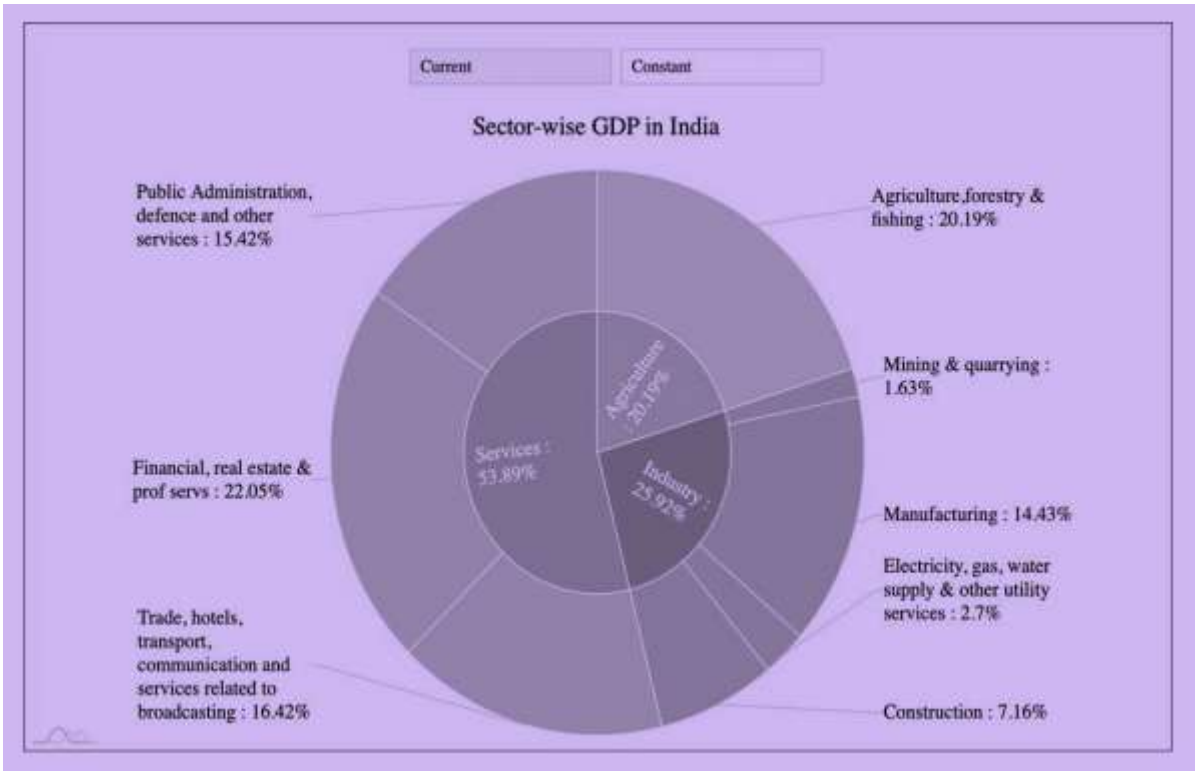

Fig.-1 India GDP sector wise

AI can play a crucial role in agriculture areas such as crop yield prediction, intelligent spraying, predictive insights, agriculture robots, crop and soil monitoring, and disease diagnosis. Early detection of crop diseases using AI/ML helps farmers control disease with proper planning, increasing crop production and income [11-15].

Fig.-2 Boll rot

Cotton is a crucial fibre and cash crop in India, providing raw materials for the textile industry. There are four main cotton species cultivated in India: Gossypium arboretum,

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Gossypium herbaceum, and Gossypium hirsutum. These species have triangular bracts, flared bracts from the bud, boll, and flower, and round, rarely with prominent shoulders. The flowers do not have a red spot at the base of the pedal, and the staminal column is short. The cultivated species include Gossypium arboretum, Gossypium herbaceum, and Gossypium hirsutum. The leaves are cut into various lobes, with bracteoles and petals. The bolls are round to moderately tapering, and the seeds are moderately large, fuzzy, and small [16-20].

AI and ML are being used in agriculture to improve data analysis, speed up decision-making, and solve complex problems. AI systems are used to improve harvest quality, help farmers determine crop choices, and optimize resource utilization. In India, agriculture contributes to 20% of the GDP, and AI-driven image processing helps farmers recognize weed species, determine crop health, and treat diseases. AI can play a crucial role in crop yield prediction, intelligent spraying, predictive insights, agriculture robots, crop and soil monitoring, and disease diagnosis. Early detection of crop diseases using AI/ML helps farmers control disease, increasing production and income. Cotton is a crucial fiber and cash crop in India [21-25].

This research focuses on the use of machine learning techniques and Artificial Intelligence (AI) to increase farmers' income and productivity in agriculture. The Indian government has committed to increasing farmers' income by securing food material in high volume with good Minimum Support Price (MSP). The government has launched initiatives to protect farmers' crops, such as crop insurance and market places. An interactive iOS app has been developed to help farmers identify crop diseases and recommend the best possible solutions [26].

The Core ML framework is based on the capabilities of iOS devices, which have the in-built high intensity GUI, allowing the iOS device to perform intensive ML algorithms with high model accuracy. The app detects Fungal Leafspot and Boll Rot diseases and works without internet or mobile data consumption. Create ML is a Mac application used to prepare the iOS model, which can be trained to perform tasks like recognizing images, extracting meaning from text, or finding the relationship between numerical values. The model was trained with 1018 images divided into Healthy, Fungal Leafspot, and Boll Rot labels. The dataset images were collected from real cotton fields over a couple of years with different types of images in different environmental conditions [27].

The image classification machine learning model recognizes images and responds with the label for that image in the data set. The model is trained with many labelled example images, collected under diverse climate conditions, lighting, and angles. The image dataset is organized using three labels – Healthy, Fungal Leafspot, and Ball Rot. The image classifier uses the scene print feature extractor to accelerate the training process and works best with real-world objects. The training session is configured by dragging the training dataset into the training data, auto splitting validation data, and dragging the testing dataset into the testing data. The UI of the training session is customizable, and the app is developed on Xcode 12.4 IDE, using Swift 5.x, and tested on iPhone 6 and iPod. The CoreML iOS framework is used for the app development [28].

Research Methodology

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The use of AI and IoT in agriculture has shown significant growth in recent years, with drones being particularly effective in pesticide spraying, minimizing crop damage, and monitoring crops from wild animals. IoT also plays a significant role in water management, with projects like SWAMP and EEWMP demonstrating water-efficient agriculture. AI and ML algorithms are essential in agriculture, with AI-based robots saving time, money, and labor. Precision agriculture improves harvest quality and accuracy, while AI applications aid in supply chain operations. However, the adoption of AI applications faces challenges due to the lack of simple solutions and seamless operation. This research aims to address this issue by developing a mobile app using TensorFlow ML models to detect cotton plant diseases. The app is simple to use and does not have complex UI/UX, allowing farmers to use the app offline without an internet connection. The TensorFlow ML model is prepared using CNN-based image classification APIs. This application helps farmers detect diseases early, take proactive action, and use recommended pesticides to overcome diseases, leading to better crop production and post-harvesting [29-30].

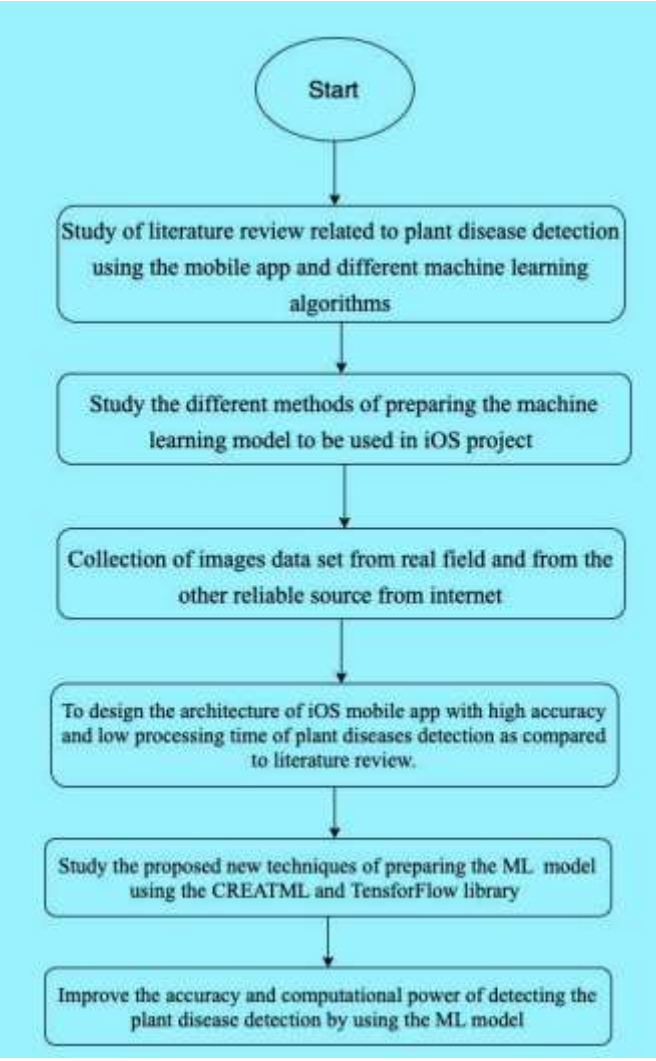

Fig.-3 Flow of Research

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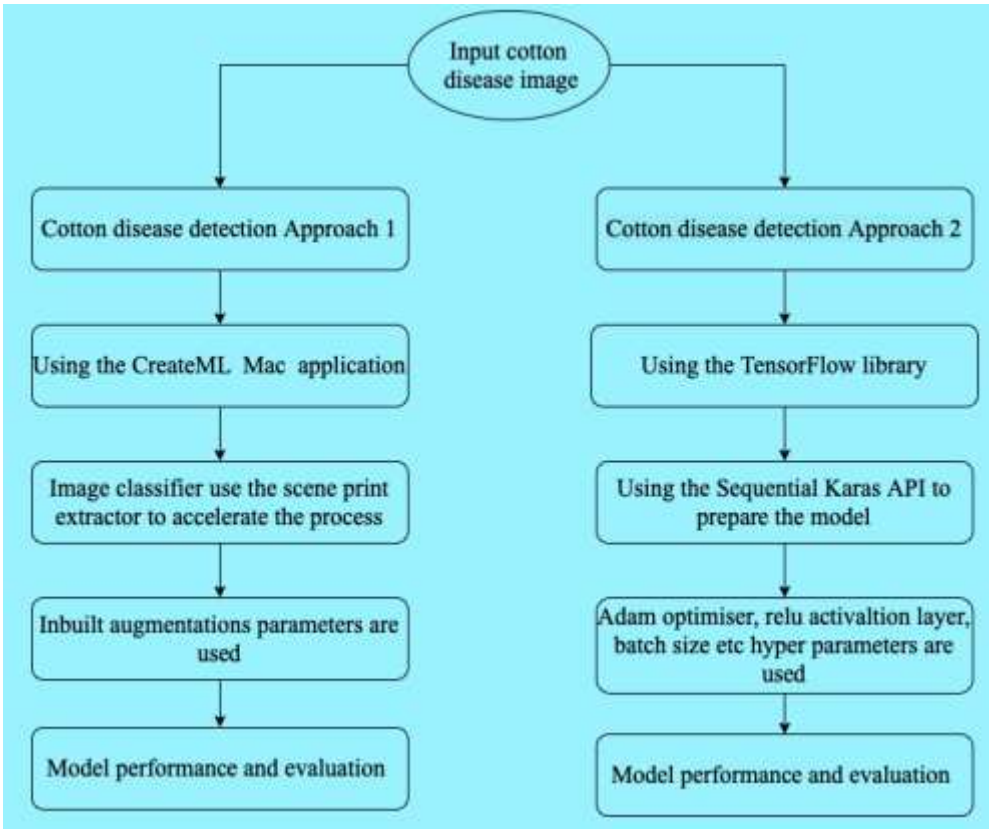

Fig.-4 Flow chart of proposed Methodologies in the presented research work

Analysis and Results

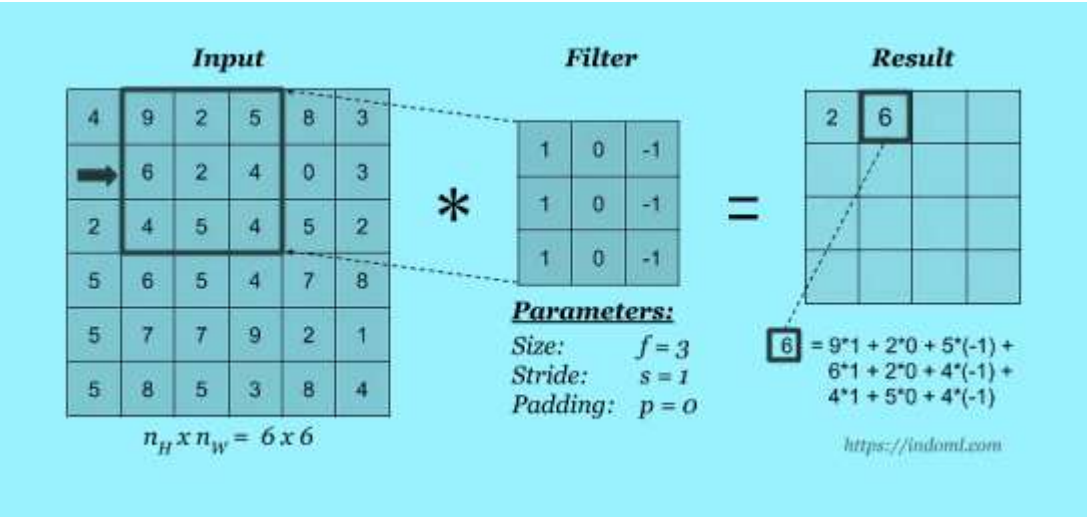

Fig.-5 Basic of convolution operation on an image

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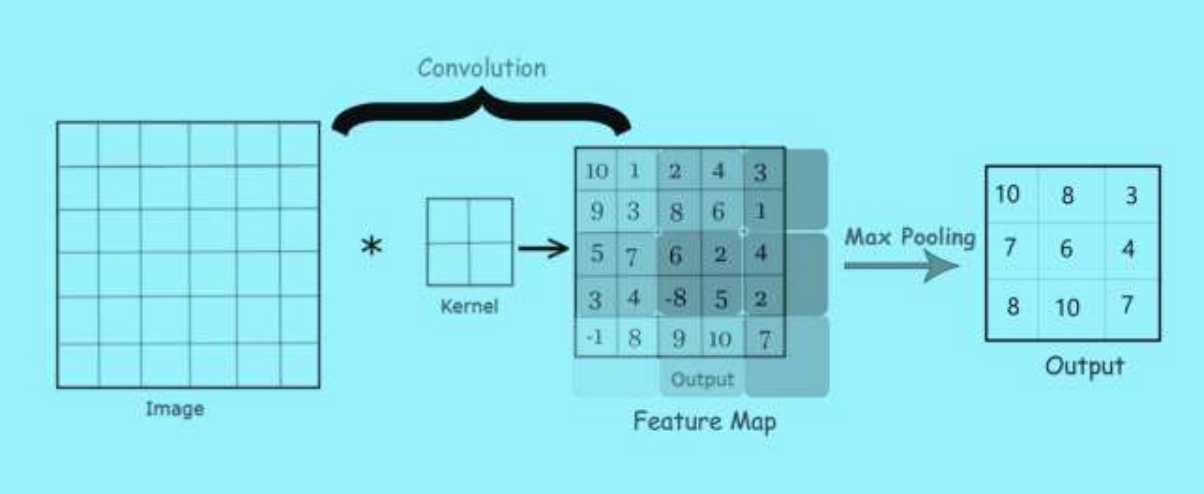

Fig.-6 Basic of max-pooling operation for image

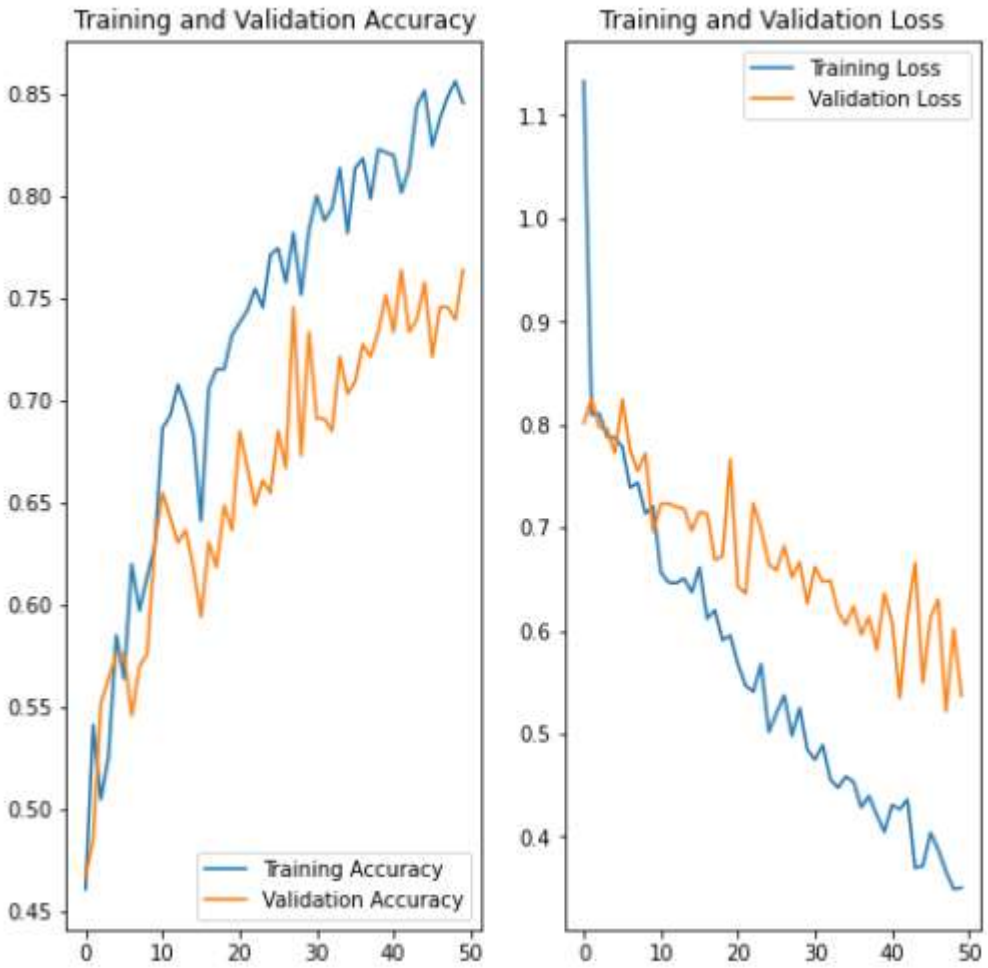

Fig.-7 Model accuracy and loss

Keras is a modular and user-friendly framework designed to simplify the implementation of TensorFlow's complex functions. It is popular due to its support for multiple programming

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languages and its development by Google. The TensorFlow framework includes several tasks, including image classification, feature extraction, activation function, pooling layers, and flattening. Image classification is supervised learning techniques that define target classes and train models to recognize them using labelled images. Feature extraction is done using a convolutional layer to extract relevant features from the input image, creating a feature map. The activation function increases the nonlinearity of the network, with Rectified Linear Unit (ReLU) and softmax activation functions used. Pooling layers compress the image to make it smaller and more adaptable. Flattening compresses the data into a long vector or column of sequentially ordered numbers. A CNN model is prepared for classification of cotton disease leaf images, using pre-processed labelled disease datasets, data augmentation, and hyper parameters tuning.

Conclusion

Cotton is a commercial crop that can provide farmers with capital and income. However, it is easily affected by diseases, leading to decreased quality and quantity. Traditionally, farmers identify crop diseases by experience, but there is no ready-made solution to check disease in the field. Machine Learning (ML) can be used to develop a model that detects cotton diseases, which can be integrated into an iOS mobile app to alert farmers. The proposed Core ML model uses an image classification approach, based on the CreateML Mac tool, and uses a labelled dataset of Boll Rot, Fungal Leafspot, and Healthy images. The model's validation accuracy is 92.3%, and its training accuracy is 92.5%. The model is converted into a Core ML model using the library's converter API, and the iOS app detects cotton diseases using the model. Future work aims to improve the accuracy of cotton disease detection by adding more disease datasets and developing a system to detect crop and weeds in the field.

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