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ENHANCING COFFEE LEAF DISEASE DETECTION WITH RMFA-CNN: A REAL-TIME MULTI-FEATURE DEEP LEARNING FRAMEWORK

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ABSTRACT

Disease prediction in coffee plants has been widely investigated with several approaches utilizing diverse features and measures. However, existing methods often fail to achieve precise classification and are affected by high false prediction rates. The research problem has more impact on the crop of plants and achieving higher yields. The research problem is contributed with a novel approach which incorporates multiple features like intensity and texture of the leaf image towards prediction. Also, the model is designed with three levels of convolution layers to reduce the feature size and supports maximizing classification accuracy. To overcome these limitations, we propose a Real-Time Multi-level Intensity Feature Analysis based Convolutional Neural Network (RMFA-CNN) for efficient disease prediction in coffee plants. The model focussed on handcraft features to be extracted with dedicated schemes of preprocessing, segmentatitaon and feature extraction where the classification is performed with CNN. In the proposed framework, plant images are first pre-processed using a region centric diagonal normalization algorithm which traverses the entire image and enhances visual quality based on intensity features. Subsequently, a gray covariance segmentation algorithm is applied to partition the image into regions according to gray level characteristics. From the segmented regions, colour and texture features are extracted and transformed into a unified one dimensional feature vector for deep CNN training. During testing, the model estimates Intensity Disease Support (IDS) and Texture Disease Support (TDS) which are further combined to compute the Disease Class Support (DCS). Based on the DCS values, the system accurately predicts the disease class. The method is evaluated with two publicly available Arabica coffee leaf datasets, namely JMuBEN and JMuBEN2, which were acquired under real-world conditions at the Mutira coffee plantation in Kirinyaga County, Kenya. Experimental results demonstrate that the proposed RMFA-CNN significantly improves classification accuracy up to 98.6 and reduces false predictions thereby enhancing the reliability of coffee plant disease prediction.

Keywords: *Disease Prediction, Coffee Plant, RMFA-CNN, DCS, Intensity Disease Support (IDS) and Texture Disease Support (TDS)*

1. INTRODUCTION

The rapid advancement of technology has transformed many sectors with agriculture being one of the most significantly impacted. Technological innovations are increasingly applied to monitor plant growth and estimate yield conditions. However, crop productivity is often reduced by the presence of diseases which negatively affect both growth and yield. Coffee, widely cultivated in humid hill regions is particularly vulnerable as high humidity promotes the onset and spread of multiple diseases. Effective monitoring and timely interventions are therefore essential to maintain healthy crop production.

Traditional manual methods of disease monitoring are prone to errors and inefficiency making them unsuitable for large scale or real time applications. Consequently, automated approaches especially those based on image processing and machine learning have gained prominence. Several classical algorithms such as Support Vector Machines

(SVM), Bayesian classifiers and neural networks have been applied to plant disease detection. While these models have achieved promising results, they face scalability challenges when dealing with large datasets. Deep learning techniques such as Long Short Term Memory (LSTM) networks and Deep Convolutional Neural Networks (DCNN) have emerged as more robust alternatives capable of handling high dimensional data while preserving essential features. Nevertheless, the accuracy of any classification approach largely depends on the choice of features and similarity measures. Traditional methods often rely on shape and texture features alone, overlooking other feature dimensions that could enhance classification accuracy.

A variety of approaches for plant disease detection and crop weed classification have been reported. Moazzam et al. [1] proposed a patch based classification model using semantic segmentation and VGG16 based CNN for weed detection. Espejo-Garcia et al. [2] combined features from pre-trained models such as Xception, Inception-ResNet, MobileNet and DenseNet followed by classification with SVM, XGBoost and logistic regression. Similarly, Jin et al. [3] applied Center-Net for vegetable detection followed by colour index segmentation and genetic algorithm based classification while Suh et al. [4] evaluated multiple architectures (AlexNet, VGG-19, ResNet, GoogLeNet, Inception-v3) for classifying sugar beet and volunteer potato under field conditions.

Other studies focused on multimodal features and hardware acceleration. Xu et al. [5] integrated RGB and depth features with AdaBoost for weed detection in wheat while Mique and Palaoag [6] used pre-trained CNNs for rice pest and disease detection. Lammie et al. [7] developed an FPGA based deep neural network integrated with IoT devices for real time weed control. Deep CNNs have also been applied for insect classification [8], weed density estimation [9] and weed detection in bell pepper fields [10].

Lottes et al. [11] developed an advanced semantic segmentation method based on fully convolutional encoder decoder network for robust crop weed detection while Kamath et al. [12] used multiple classifiers for paddy crop and weed discrimination. Al-Badri et al. [13] presented a hybrid CNN for Rumex obtusifolius and Tang et al. [14] combined k-means clustering with CNN for soybean weed detection. SegNet based semantic classification was introduced in using multispectral imagery[15]. Other contributions include comparative classifier analyses [16], transferable CNNs for multisensor imagery [17], DeepVeg for small-damage segmentation [18] and hybrid feature selection with SVM and random forest [19].

Furthermore, end to end segmentation networks such as U-Net [20], deep learning based seed sorting [21], morphology based weed classification [22] and CNN based real time classification of carrot weeds have been proposed [23]. Multi-source sensing methods [24] and remote sensing with machine learning also demonstrate the diversity of approaches being investigated [25].

Despite these advances, existing models continue to face challenges in accuracy, robustness and scalability. Many struggle to generalize across complex field conditions and exhibit limitations in real time prediction. The aim of this study is to develop an efficient Real Time Multi-Level Intensity Feature Analysis based Disease Prediction Model with CNN (RMFA-CNN) to enhance the accuracy and robustness of coffee plant disease detection. The proposed model seeks to improve image quality through a region centric diagonal normalization algorithm, segment image regions using gray covariance analysis and extract fused colour texture descriptors for CNN training. During testing, the framework integrates Intensity Disease Support (IDS) and Texture Disease Support (TDS) into a unified Disease Class Support (DCS) metric thereby enabling precise and reliable disease classification. The Intensity Disease Support (IDS) represents the support of intensity feature attracts the sample towards any disease class, and Texture Disease Support (TDS) represents the support of texture of the image attacks the sample towards any disease class. These two values are used to measure Disease class support (DCS) for any disease class. So by computing IDS, TDS and DCS towards disease prediction stimulates the accuracy of disease prediction.

1.1 Problem Statement

The methods discussed in literature have several issues:

- The existing approaches are either consider colour or texture features which challenges the efficacy of the approach in prediction.

- The methods do not consider the multiple level of features in each layer of the image which degrade the accuracy.
- As the methods consider only limited features they struggle to achieve higher accuracy in disease prediction.

2 Materials and Methods

2.1 Proposed RMFA-CNN Framework

The proposed Real Time Multi-Level Intensity Feature Analysis based Convolutional Neural Network (RMFA-CNN) was developed for accurate prediction of coffee plant diseases. The model integrates advanced preprocessing, segmentation, feature extraction, and deep learning based classification in a sequential pipeline. Figures 1 and 2 illustrate the functional workflow and system architecture, respectively.

The novelty of RMFA-CNN lies in three aspects:

a) Feature Representation: Instead of relying solely on raw pixel intensities or handcrafted descriptors, RMFA-CNN extracts multi-level intensity features that capture fine-grained variations in diseased leaf regions.

b) Preprocessing Innovation: The framework employs region-centric diagonal normalization, which aligns leaf regions along diagonals to reduce geometric distortions, and gray covariance segmentation, which enhances contrast between diseased and healthy tissues by modeling pixel covariance in grayscale space. These steps provide a more stable input representation compared to standard normalization or thresholding.

c) Integration with CNN: By embedding these enhanced features into the CNN pipeline, RMFA-CNN achieves improved generalization across varying lighting conditions, disease stages, and leaf textures.

Figures 1 illustrate the internal architecture of RMFA-CNN highlighting:

- Input Image: A leaf image with visible disease symptoms.
- Preprocessing Block: Applies geometric and statistical normalization techniques.
- Segmentation Block: Extracts disease-relevant regions.
- Feature Extraction: Generates multi-level intensity descriptors.
- RMFA-CNN Module: Integrates extracted features into a deep learning pipeline.

  Classification Output: Predicts the disease class label.

2.1.1 Data Source for Coffee Disease Detection

For this study, we utilized two publicly available Arabica coffee leaf datasets, namely JMuBEN and JMuBEN2, which were acquired under real-world conditions at the Mutira coffee plantation in Kirinyaga County, Kenya. The JMuBEN dataset is organized into three compressed folders containing diseased leaf images: 7,682 images of *Cercospora*, 8,337 images of *Rust*, and 6,572 images of *Phoma* [35].

Complementing this, the JMuBEN2 dataset consists of two compressed folders: one with 16,979 images of *Miner* and another with 18,985 images of healthy leaves. Together, these datasets provide a comprehensive representation of diseased and healthy Arabica coffee leaves.

In total, the combined datasets comprise 58,555 annotated leaf images distributed across five distinct classes (*Phoma, Cercospora, Rust, Miner,* and *Healthy*). Each image is labelled with the corresponding disease state, facilitating supervised learning approaches for classification tasks. The diversity and scale of the datasets make them particularly suitable for training and validating deep learning models, including RMFA-CNN, aimed at automated coffee leaf disease recognition. Their availability in the public domain through Mendeley Data ensures reproducibility and accessibility for further research, thereby supporting advancements in precision agriculture and plant disease management.

2.2 Image Preprocessing: Region Centric Diagonal Normalization

To enhance the quality of input coffee leaf images prior to feature extraction, we applied a Region Centric Diagonal Normalization (RCDN) algorithm.

Formally, given a coffee plant image, the algorithm initializes a diagonal window size k=3. For each pixel p, four diagonal windows are constructed. The IAV of each window is computed as the mean of pixel intensities within the window. The window with the least distance from p is identified, and the IDV is calculated as the difference between the pixel intensity and the window's IAV. If IDV<IAV/3, the pixel intensity is replaced with the IAV. The output is a normalized image N_i, which serves as the enhanced input for the RMFA CNN framework.

The region centric diagonal normalization approach normalize the image in each small window region according to the intensity feature considered on the red layer feature by computing intensity average value IAV using eq. (1) and estimates intensity distortion value IDV using eq. (3) with each distinct pixel in the regional window, based on which the pixels intensity value has been modified to maximize image quality.

Algorithm:
Given: Coffee plant image CPI.
Obtain: Normalized Image Ni
Start
Read CPI.
Initialize window size k=3.
For each pixel p
Construct four diagonal window.
For each window w
Compute Intensity Average Value (IAV) = $\frac{\sum_{i=1}^{size(W)} W(i).red}{Size(W)}$ -- (1)
End
Identify least distance window w.
w = $\underset{i=1}{\overset{4}{least}}(Dist(p.red, w(i).IAV))$ -- (2)
Compute Intensity distortion value IDV.
IDV = Dist(w.IAV,p.red) -- (3)
If IDV<w.IAV/3) then
p.red=w.IAV
End
End
Stop

2.3 Segmentation: Gray Covariance

To partition relevant features from the normalized Arabica coffee leaf images (JMuBEN and JMuBEN2 datasets), we employed the Gray Covariance Segmentation (GCS) algorithm. This method is designed to exploit pixel level gray intensity relationships, thereby enhancing the separation of diseased and healthy regions. Initially, gray feature sets were extracted from the normalized images. The algorithm then identified both peak valued and least valued gray groups, representing high intensity and low intensity regions respectively.

Algorithm:
Given: Normalized image Ni
Obtain: Segmented image Si
Start
Read Ni.
Initialize group 1 and group 2.
Gray set Gset = generate gray features of Ni.
Identify peak gray set Pgs.
Pgs $= \sum_{i=1}^{size(gset)} gset(i).value > 200$
Sort pgs according to value in descending.

Identify least gray set Lgs.
Lgs $= \sum_{i=1}^{size(gset)} gset(i).value < 200$
Sort values of lgs in descending
For each pixel p
Compute GCD on pgs pgcd.

If pgcd<lgcd then
Index p to group 1
Else
Index p to group 2.
End
End
Map group 1 features on segmented image Si.
Stop

For each pixel, the Gray Covariance Distance (GCD) was computed relative to these two groups. The pixel was subsequently assigned to the cluster with the minimum covariance distance, ensuring that local intensity variations were captured effectively. This clustering process produced segmented images where disease affected regions were distinctly separated from healthy tissue. The resulting segmentation not only reduced background noise but also optimized the images for downstream feature extraction and classification within the RMFA CNN framework.

By applying GCS to the large scale Arabica datasets (58,555 annotated leaf images across five classes: Cercospora, Rust, Phoma, Miner, and Healthy), we ensured that the segmentation process was robust across diverse disease manifestations.

2.4 Feature Extraction

Two categories of features were extracted from the segmented images to enhance the representation of disease characteristics. Colour features were derived by generating local binary patterns (LBP) which effectively capture intensity distribution across different regions of the leaf. In parallel, texture features were obtained by computing statistical descriptors that describe the surface patterns of the plant image. Together, these complementary features provided a comprehensive and discriminative representation of disease specific traits in coffee plant leaves enabling robust learning and accurate classification within the RMFA-CNN framework.

2.5 Network Architecture and Training

The RMFA-CNN architecture consisted of three convolutional layers each followed by pooling operations to progressively reduce feature dimensionality while retaining discriminative information. In the first layer, convolution was performed on local binary pattern (LBP) features to quantify binary intensity distributions. The second layer convolved segmented texture features by computing the average gray values within image quadrants. The third layer aggregated mean gray values across the entire image into a compact one-dimensional feature vector. Finally, a fully connected layer generated classification outputs corresponding to ten predefined disease classes (D1–D10). The network was trained on segmented feature inputs, with weight optimization achieved through backpropagation to minimize cross-entropy loss, ensuring robust and accurate disease prediction.

2.6 Disease Prediction

During inference, the trained network received pre-processed test images. The algorithm estimated two intermediate measures: Intensity Disease Support (IDS) and Texture Disease Support (TDS). These were fused to compute the Disease Class Support (DCS) score. The class with the maximum DCS was selected as the predicted disease label.

The intensity disease support (IDS) represent the influence of intensity feature of concern image to be classified towards any disease class and Texture Disease Support (TDS) represent the influence of texture feature of the image to be classified towards the disease class concerned. With the value of IDS and TDS, the DCS value is measured to measure the overall support of the features of image to identify the disease class.

Algorithm:

Given: DCNN trained RMFA-CNN, Test image T

Obtain: Disease Class DC

Fetch RMFA-CNN and T.

NI = region centric diagonal normalization (T)

Si = Gray Covariance Segmentation (NI)

[C,T]= perform feature extraction.

Feed features to trained network.

At convolution layer 1

Convolve local binary pattern by computing number of ones and zeros.

Apply pooling

At convolution Layer 2

Estimate quadratic gray average value to convolve into four values.

Apply pooling

At convolution layer 3

Estimate mean average value into one value.

Apply pooling

At output layer (Check the quation)

For each disease class Dc

Intensity Disease Support IDS =

$$\frac{\sum_{i=1}^{size(DC)} Dist(Dc(i).lbp.1, T.lbp.1)}{size(DC} \times \frac{\sum_{i=1}^{size(DC)} Dist(Dc(i).lbp.0, T.lbp.0)}{size(DC} - (4)$$

Compute Texture Disease support (TDS) =

$$\frac{\sum_{i=1}^{size(DC)} Dist(Dc(i).T.gmean, T.gmean)}{size(DC} - (5)$$

Estimate disease class support (DCS) $= \frac{\sum IDS}{size(DC)} \times \frac{\sum TDS}{Size(DC)} - (6)$

End

Class Dc = Choose the disease class with maximum DCS.

Stop

3 RESULTS AND DISCUSSION

The performance of the proposed Real Time Multi Level Intensity Feature Analysis based CNN (RMFA-CNN) model was evaluated for disease prediction in coffee plants. The experiments were conducted with

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varying dataset sizes (5,000, 10,000 and 20,000 samples) and compared against existing models including DeepVeg, SVM-B and CNN-SVM. Performance was analysed in terms of sensitivity, specificity, prediction accuracy, false classification ratio and time complexity.

3.1 Sensitivity Analysis

Performance on Sensitivity %			
	5000 Samples	10000 Samples	20000 Samples
DeepVeg	82	85	88.6
SVM-B	85	88	90.7
CNN-SVM	87	90	93.6
RMFA-CNN	90	94	98

Table 1: Performance Analysis Of Sensitivity

The efficacy of RMFA-CNN approach is gauged on its sensitivity according to various numbers of samples at the training class. In any class, the efficacy of the approach has been gauged and mapped with others. The RMFA-CNN algorithm achieves higher sensitivity in all the test suites used.

Fig 4 present the comparative sensitivity results. RMFA-CNN consistently outperformed benchmark models across all sample sizes. With 20,000 samples, RMFA-CNN achieved a peak sensitivity of 98%, surpassing CNN-SVM (93.6%), SVM-B (90.7%) and DeepVeg (88.6%). This improvement highlights the robustness of RMFA-CNN in correctly identifying diseased plants and minimizing false negatives. Similar results were reported by Ammavasai et al. [26] who achieved above 95% sensitivity using an optimizer-driven attention CNN for coffee disease classification. Araaf et al. [27] further demonstrated that deploying CNN models on edge devices improved detection sensitivity in field conditions, reinforcing the robustness of our approach.

3.2 Specificity Analysis

Analysis on specificity				
	DeepVeg	SVM-B	CNN-SVM	RMFA-CNN
5000 Samples	78.3	84.6	87.2	91.4
10000 Samples	82.4	87.3	89.9	94.7
20000 Samples	87.2	91.2	94.2	97.6

Table 2 Analysis On Specificity

The specificity in classification is gauged by considering different number of records in training. In each test case, the efficacy of the methods are gauged and mapped in Table 2. The RMFA-CNN model stimulates higher specificity than others.

The specificity performance is summarized in Fig 5. RMFA-CNN achieved the highest specificity across all dataset sizes, with a maximum of 97.6% at 20,000 samples, compared to CNN-SVM (94.2%), SVM-B (91.2%), and DeepVeg (87.2%). These results demonstrate RMFA-CNN’s effectiveness in reducing false positives and ensuring that healthy plants are not incorrectly classified as diseased. Comparable outcomes were found by Topal et al. [28] who emphasized improved specificity with DeepEMPR CNN while minimizing misclassifications. Abuhayi and Hajdu [29] also applied a hybrid CNN transformer successfully filtering noise and reducing false positives supporting our results.

3.3 Prediction Accuracy

Performance on Accuracy %			
	5000 samples	10000 Samples	20000 Samples

DeepVeg	82.4	85.9	90.06
SVM-B	84.8	87.7	91.66
CNN-SVM	86.6	89.7	94.6
RMFA-CNN	89.7	93.7	98.5

Table 3: Performance Analysis On Prediction Accuracy

The accuracy of different methods in disease prediction on coffee plant is gauged at varying size of samples in the training set and plotted in Table 3. The RMFA-CNN model introduces higher accuracy in all size of samples.

The prediction accuracy results are shown in Fig 6. RMFA-CNN achieved the best accuracy across all sample sizes, reaching 98.5% with 20,000 samples, compared to CNN-SVM (94.6%), SVM-B (91.66%), and DeepVeg (90.06%). Even with smaller training datasets, RMFA-CNN maintained a high accuracy (89.7% at 5,000 samples), confirming its scalability and generalization capability. This is consistent with Mansouri and Guesmi [30] who reported that transfer learning based CNNs enhanced accuracy for coffee leaf diseases. Similarly, Adelaja and Pranggono [31] proposed a real time CoffNet model that maintained strong predictive accuracy while optimizing computational cost, validating the effectiveness of RMFA-CNN. Unlike CNN based models and hybrid approaches, the RMFA-CNN model consider the intensity feature of leaf images for normalization and applies segmentation according to gray covariance which makes the approach superior in segmentation and supports achieving high quality feature extraction. On the other side, by measuring intensity orient disease support and texture orient disease support in predicting the disease, the RMFA-CNN model achieves higher accuracy in disease prediction.

3.4 False Classification Ratio

False Classification Ratio %			
	5000 samples	**10000 Samples**	**20000 Samples**
DeepVeg	17.6	14.1	9.94
SVM-B	15.2	12.3	8.34
CNN-SVM	13.4	10.3	5.4
RMFA-CNN	10.3	6.3	1.5

Table 4: False Classification Ratio

The poorness in classification introduced by different approaches are gauged and plotted in Table 4. The proposed RMFA-CNN algorithm down line the ratio than others.

Fig 7 illustrates the false classification ratio (FCR) across methods. RMFA-CNN consistently demonstrated the lowest FCR, with only 1.5% at 20,000 samples, compared to CNN-SVM (5.4%), SVM-B (8.34%), and DeepVeg (9.94%). The reduced FCR reflects the reliability of RMFA-CNN in minimizing misclassifications, a critical factor in real-world agricultural applications. Abuhayi and Hajdu [29] also reported suppressed error rates using a hybrid compact CNN-transformer while Selvanarayanan et al. [32] demonstrated early *Colletotrichum* detection with minimized false positives confirming our findings.

3.5 Time Complexity

The performance of various approaches are gauged for their time complexity and plotted in Table 5. In each test case, the RMFA-CNN approach introduces least value than others.

RMFA-CNN exhibited the lowest computational cost among the evaluated models (Fig 8). For 20,000 samples, RMFA-CNN required only 5.3 seconds, compared to CNN-SVM (8.6 s), SVM-B (10.5 s), and DeepVeg (18.1 s). This efficiency demonstrates RMFA-CNN's suitability for real-time disease detection in large-scale deployments and proved efficient model compared to existing methods. This efficiency is in line with Silva et al. [33] who developed a

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YOLOv8-based low-cost deep learning approach for coffee leaf disease localization. Similarly, Yoseph [34] emphasized the importance of reducing CNN complexity for Ethiopian coffee leaf detection further validating the efficiency of RMFA-CNN.

Analysis on time complexity				
No of samples	**Deep Veg**	**SVM-B**	**CNN-SVM**	**RMFA-CNN**
5000 Samples	5.4	3.2	2.8	2.1
10000 Samples	11.2	5.4	3.7	2.5
20000 Samples	18.1	10.5	8.6	5.3

Table 5: Time complexity

3.6 Difference From Prior Work

The proposed model differs from previous works in several ways. First, the pre-processing of the leaf image is performed by applying region centric diagonal normalization which adjust the image quality according to Intensity Average Value (IAV), Intensity Distortion Value (IDV) which maximize the image quality in each layer of the image. Further, the segmentation is performed using gray covariance segmentation. On the other side, the method extracts intensity and texture features towards classification of the image. By incorporating multiple features in classification, the performance of the approach is greatly improved.

4. CONCLUSION

Experimental results demonstrated that RMFA-CNN consistently outperformed existing approaches achieving up to 98.5% accuracy, 98% sensitivity and 97.6% specificity while maintaining a low false classification rate and reduced time complexity. These outcomes highlight the robustness and efficiency of the proposed method in real-time applications making it highly suitable for deployment in large scale coffee farming environments. Beyond improving prediction accuracy, RMFA-CNN has the potential to support early detection, timely intervention and sustainable crop management ultimately contributing to enhanced coffee yield and reduced economic losses. Future research will focus on extending the model to handle multi-crop disease classification, incorporating edge computing and IoT devices for on-field deployment and further improving scalability under diverse environmental conditions. As the model consider multiple features like intensity and texture of the leaf images, the quality of pre-processing and segmentation is greatly improved. This supports the maximization of prediction accuracy and would support the yield estimation in future.

The proposed model is adaptive for varying kind of image quality and the accuracy of the model does not vary in more ratio. However, it is necessary to collect varying quality of plant image to achieve more accuracy. On the other side, the work has limitations on the colour images of coffee plants.

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Figures:

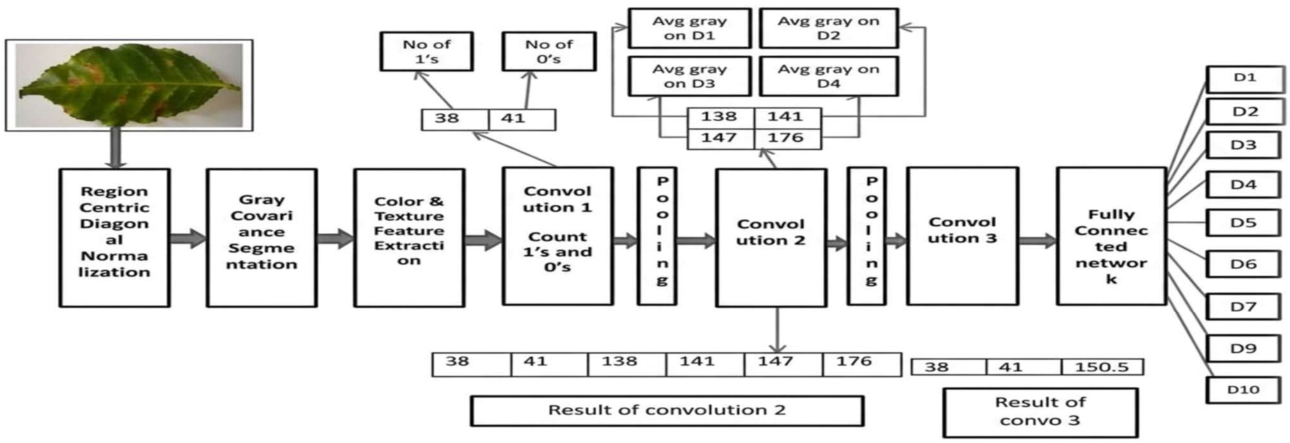
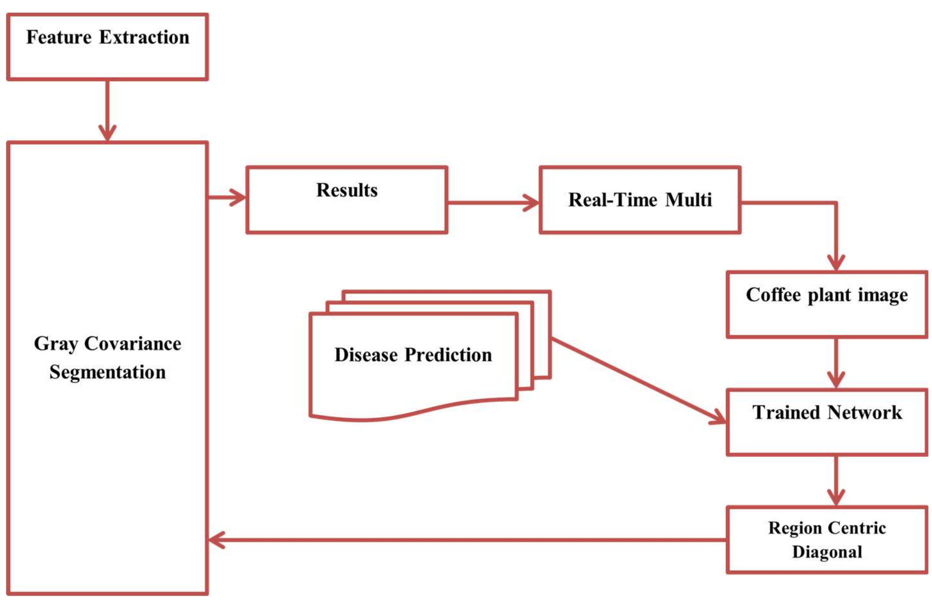


Fig. 1: Functional Diagram of RMFA-CNN Model

Fig 2:



Architecture of RMFA-CNN model

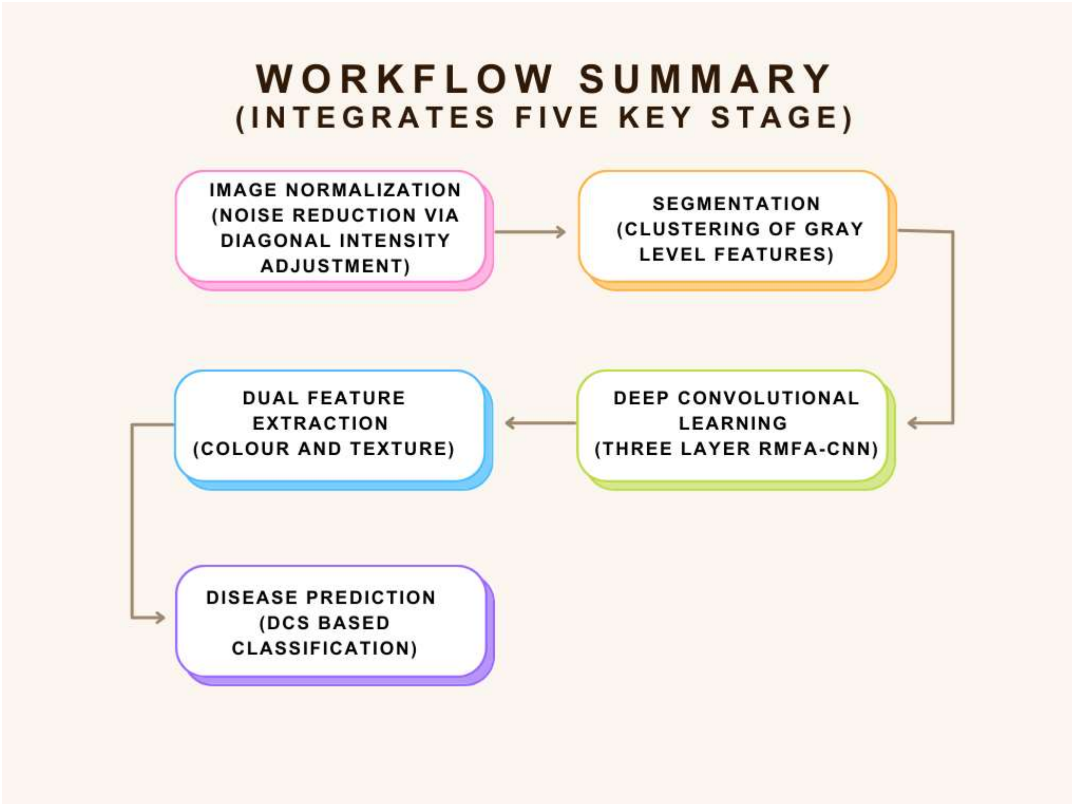


Fig 3 : Workflow Of RMFA-CNN Model

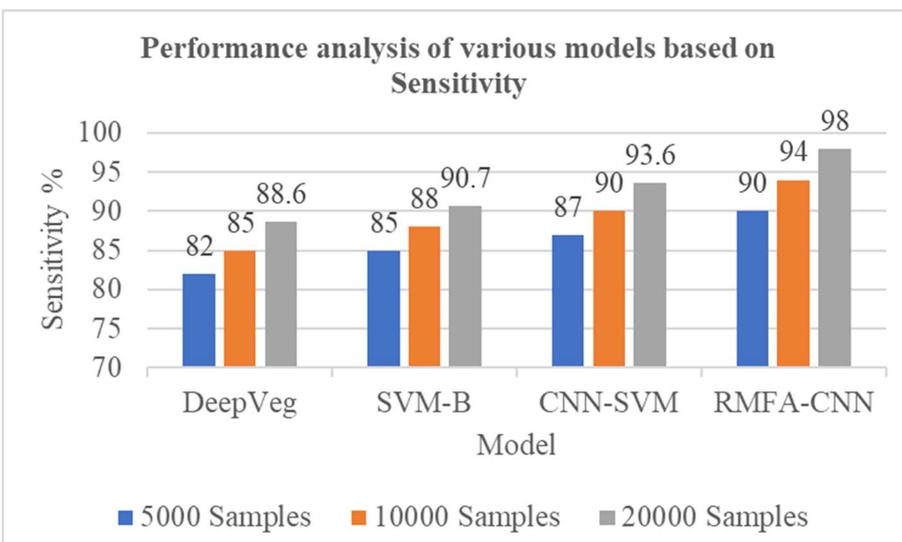


Fig 4: Performance Analysis Of Various Models Based On Sensitivity

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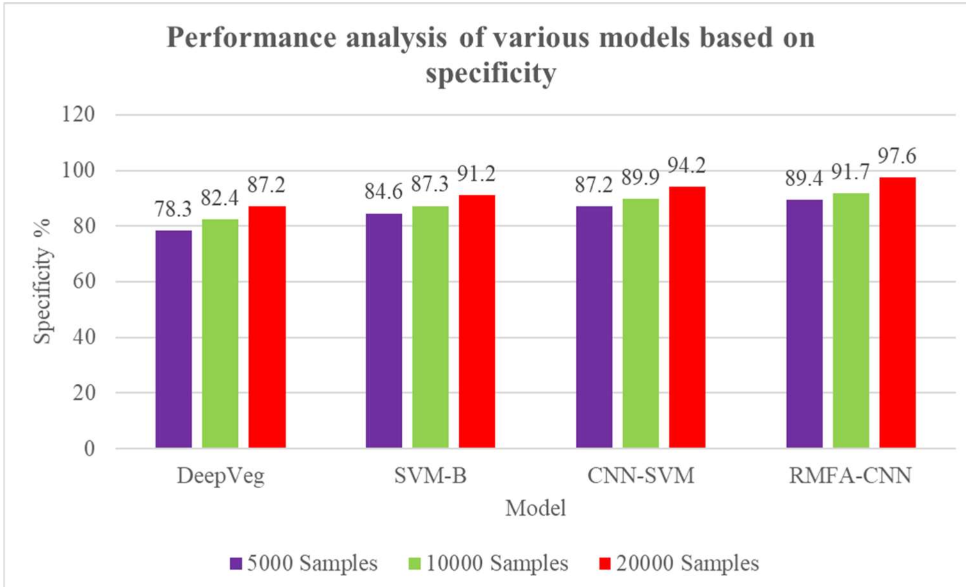

Fig 5: Performance Analysis Of Various Models Based On Specificity

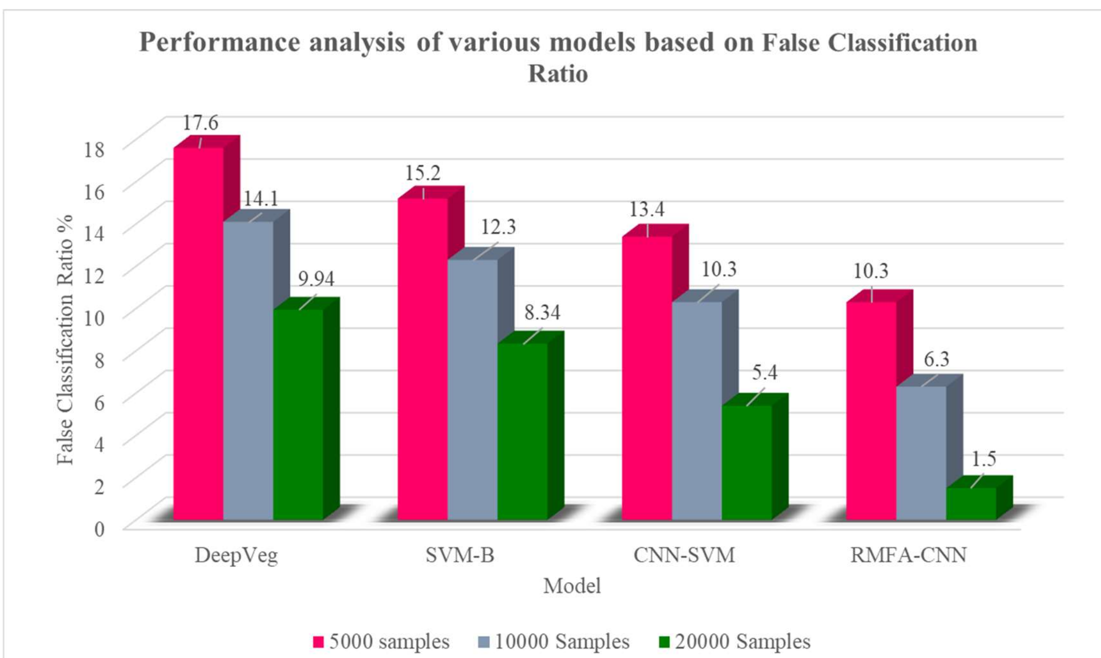

Fig 6: Performance Analysis Of Various Models Based On Prediction Accuracy

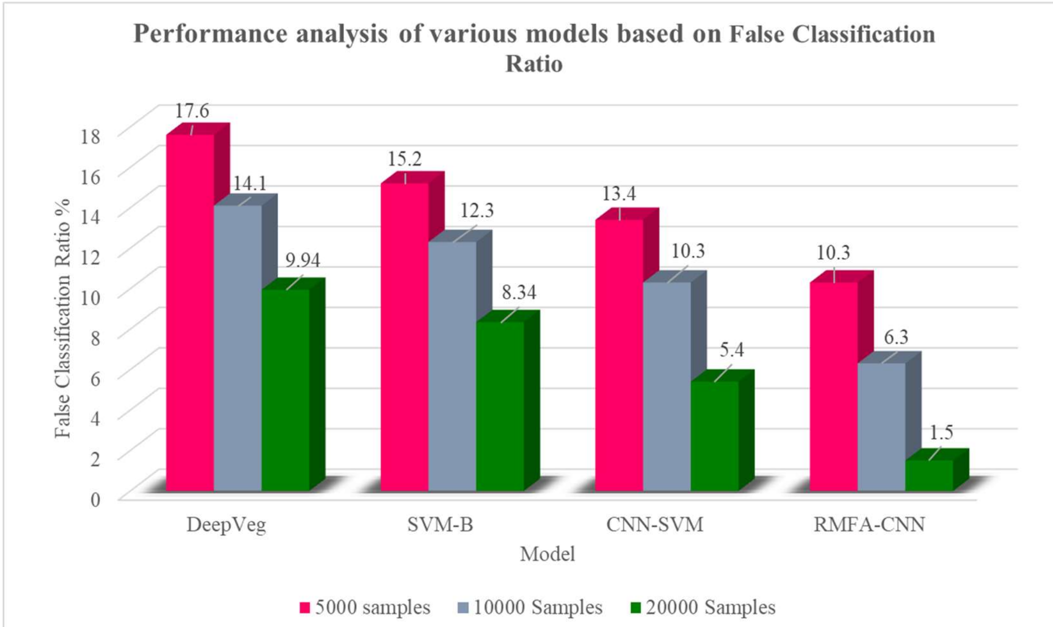

Fig 7: Performance Analysis Of Various Models Based On False Classification Ratio

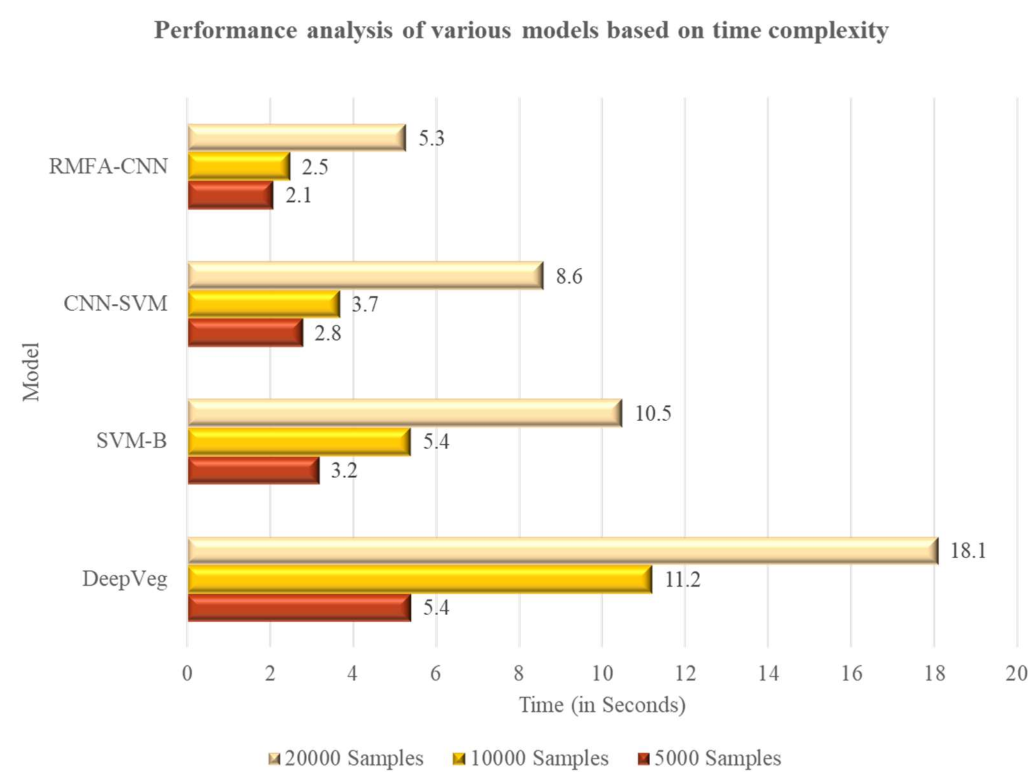

Fig 8: Performance Analysis Of Various Models Based On Time Complexity