Journal of Computational Analysis and Applications VOL. 33, NO. 7, 2024

10.48047/jocaaa.2024.33.07.33

Multi-Spectral Image Fusion with Efficient Net and Novel Feature Extraction for Enhanced Disease Detection in Sal and Tendu Leaves

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Abstract: The detection of diseases in the leaves of Sal and Tendu is very crucial as these plants carry economic and ecological importance. Traditional methods of plant disease detection essentially rely on RGB images that are capable of capturing only visible symptoms, not the early symptoms or hidden stress indicators. These techniques cannot identify the micro-level indicators of diseases in terms of shape deformation, texture anomalies, and color changes. To overcome such deficiencies, we propose a multi-modal fusion model that integrates multi-spectral imaging with advanced feature extraction techniques to enhance the possibility of detecting diseases. Our method starts with the fusion of multi-spectral and RGB images, integrating spectral bands like near Infrared and shortwave infrared for the early detection of diseases. In the methods followed, Local Binary Patterns are used to make detailed textures, Zernike Moments as strong shape descriptors, and the CIELAB color space, considering perceptually uniform color representation, is applied in feature extraction. These features are combined into a multi-dimensional vector to capture comprehensive disease characteristics. For the classification process, we adopt EfficientNet and utilize transfer learning for enhancement of classification accuracy without sacrificing too much computational costs. These merged features from pre-trained EfficientNet models result in a strong model capable of achieving an accuracy of 92-97%, and an F1-score in between 0.9-0.95 values, thus really outperforming the traditional models. Such an approach proves to be superior at enhancing disease-detection accuracy while simultaneously affording scalability, thus further leading to applications in real-time monitoring systems. Therefore, it proves to be conducive to better disease management and, more importantly, the salvation of Sal and Tendu species.

Keywords: Multi-Spectral Imaging, Efficient Net, Local Binary Patterns, Zernike Moments, Plant Disease Detection

1. Introduction

Identification and control of diseases in plants is critical and should not be overlooked for the economically and ecologically important species Sal (Shorea robusta) and Tendu (Diospyros melanoxylon) for the very sustenance of healthy forests and related industries. These species play a role in ecological balance and provide for livelihoods through the production of non-timber forest products such as leaves used for medicinal purposes [1, 2, 3] and as wrappers for the tendu leaves produced by the Indian bidi industry sets. Blight, fungal infections, and bacterial spots affecting these leaves can cause significant yield loss and quality degradation. It is primarily at such a juncture that issues related to disease identification become important for the quick implementation of remedies and proper management. Conventional methods in plant disease diagnosis mainly rely on RGB images acquired by using routine cameras. Even though these techniques have some points of advantage like ease of data acquisition and handling, they often ignore early symptoms of the disease, which might be valid only in the spectral ranges other than the visible range. Another limitation of RGB-based detection systems lies in slight texture, shape, and color changes that still cannot provide detailed understanding of the disease by the system. All these limitations cause a need for more complex techniques capable of detecting information about different spectral ranges,

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and delivering more in-depth analysis of symptoms. Addressing the issues, this paper proposes a multi-modal data fusion approach based on RGB and multi-spectral imaging for a more detailed view of disease symptoms. Multi-spectral imaging, incorporating near Infrared (NIR) bands and shortwave infrared (SWIR), had the benefit of such information in the bands that are not invisible to the human eye but can only be captured with the aid of multi-spectral imaging process. Further improving early disease detection [4, 5, 6], RGB and multispectral data fusion is performed through advanced image alignment techniques, namely Scale Invariant Feature Transform and homography. Then feature fusion through CNNs gives a coherent representation of the status of the leaf. In addition to the multi-modal data fusion used in the proposed method, new feature extraction techniques have been designed for extracting texture, shape, and color variation in leaves. Fine-grained texture information is deployed using Local Binary Patterns (LBP) as it is very important for detecting surface irregularities induced due to the same fungal infections. Zernike Moments are thus applied to furnish powerful shape descriptors, which give rotational invariance and help in the shape distortions that are an indication of diseases like blight. The CIELAB color space-based perceptually uniform color space helps further analyze color changes associated with the progress of the disease. We used the power of transfer learning to classify diseases accurately with the EfficientNet model. It is an advanced CNN model providing superior performance for the image classification task with fewer parameters and lower computational costs. In this case, a pre-trained EfficientNet that is fine-tuned on a labeled Sal and Tendu leaf image dataset enhances the model's ability to detect and map many diseases correctly. Significant improvement in the accuracy of disease detection compared with traditional methods is obtained through an integrated approach that integrates multi-spectral data, handcrafted features, and transfer learning.

Motivation & Contribution

The work was motivated by the need to transcend the suboptimalities inherent in traditional plant disease detection, as experienced for example with Sal and Tendu leaves. Such approaches based heavily on RGB imaging cannot identify the symptoms in earlier stages of disease because signs appear in spectral ranges beyond visible light. Moreover, general techniques usually fail to differentiate between minimal variations of texture, color, and shape that characterize different diseases. The far-reaching implications of these limitations are the early or incorrect detection, which can cause huge economic losses. In fact, losses are largely considerable in streams and industries relying on the quality Sal and Tendu leaves, such as medicine and bidi. Hence, there is a critical need for a more generalized and accurate disease detection method for these species which can integrate spectral bands of data and capture the finer features of the sequence of disease progression. Several key contributions of this work lie in the advance of plant disease detection research. It introduces a novel multi-modal data fusion approach that combines RGB with multi-spectral imaging, capturing more extensive ranges of disease symptoms, some which cannot be seen naked. The method proposed incorporates spectral bands like NIR along with SWIR to provide early detection of plant stress and decay. Certainly this is much better than any form of technique dependent on RGB alone. The paper has come out as a novel method of feature extraction combined with Local Binary Patterns (LBP) for texture analysis, Zernike Moments for the detection of shape, and with the CIELAB color space for enhanced color representation. Taken together, these techniques then offer a more detailed and robust analysis of the condition of the leaf. For, subtle texture, shape, or color changes characterize disease. Introduction As mentioned previously, the yield of correct classifications is dominated much by the efficiency of the model. Finally, the combination of transfer learning with EfficientNet in the classification model is used innovatively in plant disease detection. The proposed system is able to attain higher accuracy and efficiency in the classification process as compared to conventional models by fine-tuning a pre-trained EfficientNet model with multi-modal data and

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handcrafted features. Using transfer learning reduces the requirement for large training datasets and enables the model to exploit knowledge in large image repositories such that the final performance of the model is improved. This work can ultimately contribute to the development of more accurate, efficient, and scalable solutions in plant disease detection with the potential of being used as a real-time monitoring system in the forest management and agriculture industries in process.

2. Review of Existing Models for Leaf Disease Analysis

In the last few decades, artificial intelligence and machine learning have matured, and their applications in this field have gained momentum. Considering the increasing population of the world and ever-increasing importance of agricultural productivity, there is an urgent need to have a more accurate detection systems of diseases at earlier stages of pathology to prevent loss in crops and enhance food security. Traditional detection of plant diseases is time-consuming, costly, and inaccurate. As such, researchers are now working on developing deep learning, image processing, and sensor-based technologies in developing efficient, scalable, and automated methods for identifying and classifying the different plant diseases in real-time or near-real-time scenarios. This review made a broad analysis of recent developments in the area of detection of plant diseases. Different methods and techniques applied in these studies include convolutional neural networks (CNNs), generative adversarial networks (GANs), residual networks, transfer learning, and sensor-based systems. Most of these methods have shown to a certain extent a success rate in the detection of diseases in crops like tomatoes, groundnuts, apples, grapes, and many others. Each approach focuses on one of the facets of disease detection, like increased accuracy in detection, minimizing false positives, or even improving processing rates, while still making the technology possible through mobile applications or the IoT integration process. This sequence of studies shares a common thread, that is, the use of convolutional neural networks (CNNs), deep learning architecture that is most efficiently used for image-based tasks such as plant disease identification. For example, work published by Garg et al. [1], in which the authors have integrated IoT-enabled sensors with a machine learning approach to predict leaf spot disease in groundnuts. This method performed well up to a significantly good accuracy of 89% but was applied only to a few environmental conditions and one type of crop only. Nevertheless, in more advanced CNN models like that used by Zhou et al. [2] in the tomato leaf disease detection system has successfully reached a tremendous accuracy of 94.8% through the employment of deep residual dense networks which exhaustively capture both local as well as global features of leaves & samples. However, the model had its own set of disadvantages as it required an inordinate amount of training data to generalize over multiple kinds of diseases.

Other works include Zhu et al. [3], which is lightened for disease detection, where asymmetric convolution combined with dilated convolutions were used in LAD-Net, focusing on real-time classification of apples' leaf pests and diseases. Even though it reaches an accuracy of 91.5% the lightweight model was not well generalized for use in other than apple leaves; this is to show that even though models applied in a specific application may have a problem in scaling to different crops. Hosny et al. [4] combined CNNs with Local Binary Pattern (LBP) features to advance a multi-class classification model for accurate detection of different plant diseases. The model presented by them is efficient, as it attained a classification accuracy of 92.1%, though the same is computationally expensive as well, as it is built by integrating two multiple feature extraction approaches. In fact, models such as VMF-SSD developed by Tian et al. [5] with the integration of multi-scale feature fusion provide further advancement into increasing the accuracy of disease detection. They have actually managed to show multi-scale fusion capabilities using their method in an application on apple leaf diseases, capturing finer details and reaching an accuracy of 90.6%.

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Even so, this approach remains very specialized for specific crops and diseases and consequently limited in its adaptability towards more generalized agricultural systems. Furthermore, some articles such as Bijoy et al. [6] discussed the application of deep convolutional neural networks (dCNN) for leaf diseases in rice. Their model achieved 93.2% accuracy, proving deep learning models are robust in crop-specific applications, but unlike the above models, this model lacked the capacity to incorporate multi-modal data to arrive at improved results. A number of research studies deal with the promising use of attention mechanisms for improvement in the accuracy and recall of the models developed for plant disease detection. The classification of diseases found in pepper leaves was done by using a self-attentive convolutional network as a GSAtt-CMNetV3, and the classification accuracy achieved was 88.7%. The proposed method, though dependent on attention-based feature extraction, suffered from scalability and real-time performance issues when dealing with larger datasets. Zhao et al. [8] reviewed the GANs usage in the generation of synthetic images of leaves, thus improving the models trained with generated data for plant disease detection although its real-word usage is extremely limited due to its dependency on synthetic samples.

One of the more promising applications of transfer learning and multi-agent systems is in plant disease detection. Recently, Allaoua Chelloug et al. have reported an excellent application of this method in the identification of leaf diseases using 3D leaves and deep reinforcement learning with class and severity estimation. This versatility brings great benefits in the case of precision agriculture, since realizing the intensity of a disease occurs almost simultaneously with discovering its existence. However, the complexity of the model in reaching up to 86.2% accuracy brings problems concerning real-time performance and scalability to bigger agricultural systems. The advent of IoT technology, along with mobile apps, has also widened the scope of accessibility of plant disease detection. For instance, Rashid et al. [21] demonstrated IoT-based multi-model deep learning methods for early disease detection in corn. Using IoT sensors with the decision-level fusion of CNN architectures like AlexNet and VGG-16, their approach achieved 90.3% accuracy while bringing a new challenge of complexity when managing heterogeneous data sources. Similarly, Salam et al. [13] demonstrated the potential of mobile-based detection systems with CNN-based Mulberry leaf disease detection app with an accuracy of 88.1%. Though such mobile solutions are very accessible, they are still limited by hardware restrictions that can impact both the speed and precision across different contexts. From the reviewed papers, it can be observed that each method has its own strengths in a particular context or crop disease type. However, those approaches have also presented numerous limitations, such as the complexity in computing, poor generalization capabilities across a wide-ranging variety of crops, and their difficulty of application in real time. Models based on deep learning architectures like CNNs and transfer learning steadily outperformed the classical methods, especially for single-crop disease detection scenarios. However, scalability and adaptability remain big challenges, mainly when trying to extend these models into multi-crop and multi-disease detection.

Reference	Method Used	Main Objective	Findings	Results	Limitations
[1]	IoT-Enabled Sensors	Monitor soil and environmental factors for groundnut leaf spot disease	IoT sensors effectively capture disease-relevant parameters	Improved disease germination prediction with 89% accuracy	Limited to groundnut leaf spot disease
[2]	Restructured Deep	Identify tomato leaf	Deep residual dense networks perform	Achieved 94.8%	Requires extensive

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	Residual Dense Network	diseases	well for identifying tomato diseases	accuracy in tomato leaf disease classification	training data for generalization
[3]	LAD-Net	Classify apple leaf pests and diseases in real-time	Lightweight model with asymmetric convolution performs well for real-time classification	91.5% accuracy in apple leaf disease classification	Lacks robustness in non-apple leaf datasets
[4]	CNN + LBP Feature Fusion	Multi-class classification of plant leaf diseases	Feature fusion of CNN and LBP improves disease detection	92.1% classification accuracy for multiple plant diseases	Increased computational complexity with fused features
[5]	VMF-SSD	Detect apple leaf diseases using multi-scale feature fusion	Multi-scale fusion enhances detection in complex environments	90.6% accuracy in apple leaf disease detection	Suboptimal performance with non-apple crops
[6]	dCNN	Detect rice leaf diseases	Deep CNN models provide robust detection in rice diseases	93.2% accuracy in rice disease detection	Lacks multi-modal data integration for enhanced accuracy
[7]	GSAtt-CMNetV3	Classify pepper leaf diseases using osprey optimization	Self-attentive mechanisms enhance classification performance	88.7% accuracy in detecting bacterial spot disease	Struggles with larger datasets and real-time performance
[8]	DoubleGAN	Generate synthetic leaf data for plant disease detection	GAN-generated leaves improve disease detection performance	87.9% detection accuracy with synthetic leaves	Limited real-world application due to reliance on synthetic data
[9]	LeafNet	Groundnut leaf disease detection using deep learning	Weight initialization and residual connections improve disease classification	Achieved 90.5% accuracy in groundnut leaf disease detection	High computational costs with deep networks
[10]	MULTINET	3D plant leaf disease identification and severity estimation	Dual segmentation enhances severity estimation in 3D	86.2% accuracy in plant leaf disease identification	Difficulty handling real-time 3D data processing
[11]	YR2S	Detect and	Efficient deep	91.8%	Requires fine-

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		classify plant leaf diseases	learning model with optimized feature attention	accuracy with YOLOv7-based classification	tuning for non-pretrained datasets
[12]	Multi-step Preprocessing + UNet	Detect pepper bell leaf diseases using segmentation and transfer learning	Transfer learning models effectively classify pepper leaf diseases	93.5% classification accuracy	High dependency on segmentation quality
[13]	CNN-Based Smart Android App	Mulberry leaf disease detection using mobile devices	MobileNetV3Small facilitates mobile-based disease detection	88.1% accuracy in detecting mulberry leaf diseases	Limited by hardware capabilities of mobile devices
[14]	Plant-Leaf Disease Classifier	Compare traditional and deep learning methods for leaf disease classification	Deep learning models outperform traditional methods in accuracy	92.4% accuracy using CNN-based models	Traditional methods are inefficient for complex datasets
[15]	PiTLiD	Identify plant diseases from leaf images	CNN-based models provide robust disease classification	90.8% accuracy in identifying leaf diseases	Limited performance in noisy datasets
[16]	Lightweight Deep Residual Network + Attention Mechanism	Detect leaf diseases using deep residual networks	Attention mechanisms improve disease classification performance	89.4% accuracy in detecting multiple leaf diseases	Struggles with real-time processing in large datasets
[17]	MobileNet	Classify bean leaf diseases using mobile deep learning	Lightweight models suitable for mobile applications	Achieved 85.9% accuracy in bean leaf disease classification	Limited dataset coverage for other crops
[18]	Capsule Network + Residual Network	Classify plant leaf diseases	Capsule networks improve robustness to data variability	92.7% accuracy in leaf disease classification	Computational complexity increases with capsule networks
[19]	Deep Neural Networks	Detect citrus fruit and leaf diseases	DNNs provide robust citrus disease detection	88.5% detection accuracy for citrus leaves and fruit	Limited generalization to non-citrus crops

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[20]	CNN + Dataset Development	Detect plant diseases using real-time datasets	Real-time dataset improves disease detection models	89.9% accuracy in real-time plant disease detection	Difficulties in adapting the model to other datasets
[21]	IoT + Deep Learning	Early detection of corn plant leaf diseases	IoT sensors combined with CNN models improve corn disease detection	90.3% accuracy in corn leaf disease detection	IoT integration increases system complexity
[22]	Inception-ResNet + Shuffle-Transformer	Detect grape leaf diseases using feature fusion	Dual-track fusion improves feature representation for grape leaf disease	91.2% accuracy in grape disease detection	Performance decreases with complex leaf structures
[23]	Deep Learning + Transformers	Identify tea leaf diseases in natural environments	Transformer-based models perform well in complex environments	86.7% accuracy in tea leaf disease classification	Struggles with real-time performance in varying conditions
[24]	YOLOv8	Lightweight grape leaf disease detection	YOLOv8 achieves efficient grape leaf disease detection	89.5% detection accuracy using lightweight YOLOv8	Limited performance in identifying minor lesions
[25]	SPEDCCNN	Segment crop leaf diseases using encoder-decoder networks	Spatial pyramid and encoder-decoder networks enhance segmentation	87.2% accuracy in crop leaf disease segmentation	High computational demand for large datasets

Table 1. Comparative Analysis of Existing Methods

A comprehensive review of these papers will look to widen the horizon by putting forward significant advances in detection of plant diseases using deep learning, transfer learning, and multi-modal sensor integration. On a general basis, CNNs and other deep learning models have been demonstrated to have higher accuracy than conventional machine learning techniques for all crops and disease conditions. Recently, promising for minimizing the large and extensive training datasets, which is one of the common bottlenecks found in most applications related to agriculture, is the use of transfer learning. However, the above limitations noted in most of the studies suggest that there are improvements in accuracy and precision but much discrepancy exists in developing models adaptable, scalable and with real-time detection of diseases across crops and environments. One of the most important results is an increase in reliance on feature fusion and attention mechanisms, such as those in VMF-SSD [5], GSAtt-CMNetV3 [7], and others, demonstrating that multi-scale and self-attentive models contribute additionally to detecting more complex disease patterns. On the other hand, this increases the computational complexity. Additionally, while GAN-generated leaf images have shown promising potential for improving training sets, the demand for synthetics poses a significant challenge for the transferability of such models to real-world applications in which

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natural variability significantly impacts these scenarios. The second notable point is that the implementation of IoT-based systems and mobile applications for detecting plant diseases is on the rise. According to Rashid et al. [21], and Salam et al. [13],. These developments make disease detection solutions a reality for farmers and other people engaged in agriculture, allowing these professionals to monitor in real time and portably the health of plants. Such systems are highly hardware-dependent and are troubled by the integration of heterogenous sources of data, which affects the performance and scalability of the system. More importantly, real-time applications, which include the 3D multi-agent system proposed by Allaoua Chelloug et al. [10], create new ways to assess disease severity but their complexity may represent a restriction to other developing settings. Conclusion While significant strides have been taken in improving the accuracy and efficiency of plant disease detection through deep learning and sensor technologies, much more research is necessary in developing models that are not only accurate but also adaptable, scalable, and computationally effective. Future studies should focus more on fusing multi-modal data from multiple sensors and improve generalization capabilities across various agricultural environments. Other envisioned features, therefore, of real-time and mobile-based applications are to continue to play an important role in bringing forth the next generation of disease detection technology for the cutting-edge edge of precision agriculture, though further optimization in such tools is deemed necessary to ensure that they are deployable at scale without losing in accuracy or performance.

3. Proposed Design of an Improved Multi-Spectral Image Fusion Model with EfficientNet and Novel Feature Extraction for Enhanced Disease Detection in Sal and Tendu Leaves

This section discusses design of the Improved Multi-Spectral Image Fusion Model with EfficientNet and Novel Feature Extraction for Enhanced Disease Detection in Sal and Tendu Leaves to overcome issues that pervade the existing methods, including low efficiency and high complexity. From figure 1, the developed method for disease detection from Sal and Tendu leaves can be very well said to be multilayered, where multi-spectral imaging is bridged with advanced feature extraction techniques, and the CNN transfer learning is utilized for the improvement of classification accuracy. In this, it is using the fusion of multi-spectral imaging data as well as RGB features for providing an all-around view of disease symptoms. It also integrates the LBP for texture analysis, Zernike Moments for the shape descriptors, as well as the CIELAB color space for color variation detection. Using transfer learning, EfficientNet, a state-of-the-art CNN model, is employed for optimal classification performance. Multi-spectral data cued with RGB features begin by capturing a combination of data from both a standard RGB camera and a multi-spectral sensor capturing bands like near Infrared (NIR) and shortwave infrared (SWIR). The multi-spectral information offers some key information about the health of the leaf that goes unnoticed in the RGB spectrum, stress and decay markers. The RGB images are represented as IRGB(x,y), where 'x' and 'y' are spatial coordinates, and the multi-spectral images are represented as IMS(x,y,λ), where λ is used to represent the wavelength bands in the multi-spectral ranges. The very first step of the process is the alignment of the RGB and multi-spectral images & samples. This is done through feature-matching techniques such as Scale Invariant Feature Transform (SIFT) process. This feature matching is, thus, mathematically formulated based on key point extraction of the RGB image PRGB and the multi-spectral image PMS using the scale-space representation via equation 1,

$$S(x, y, \sigma) = I(x, y) * G(x, y, \sigma) \ldots (1)$$

Where, S(x,y,σ) is the scale-space representation, ∗represents convolution, and G(x,y,σ) is the Gaussian kernel defined via equation 2,

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$$G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \ldots (2)$$

The key points are matched based on their descriptors, and a transformation matrix 'H' (homography) is estimated to align the images& samples. This transformation matrix is given via equation 3,

$$H = \begin{bmatrix} h11 & h12 & h12 \\ h21 & h22 & h23 \\ h31 & h32 & h33 \end{bmatrix} \ldots (3)$$

The transformation matrix 'H' is applied to warp the multi-spectral image onto the RGB image via equation 4,

$$I\left(MS\left(aligned(x', y', \lambda)\right)\right) = IMS(H(x, y), \lambda) \ldots (4)$$

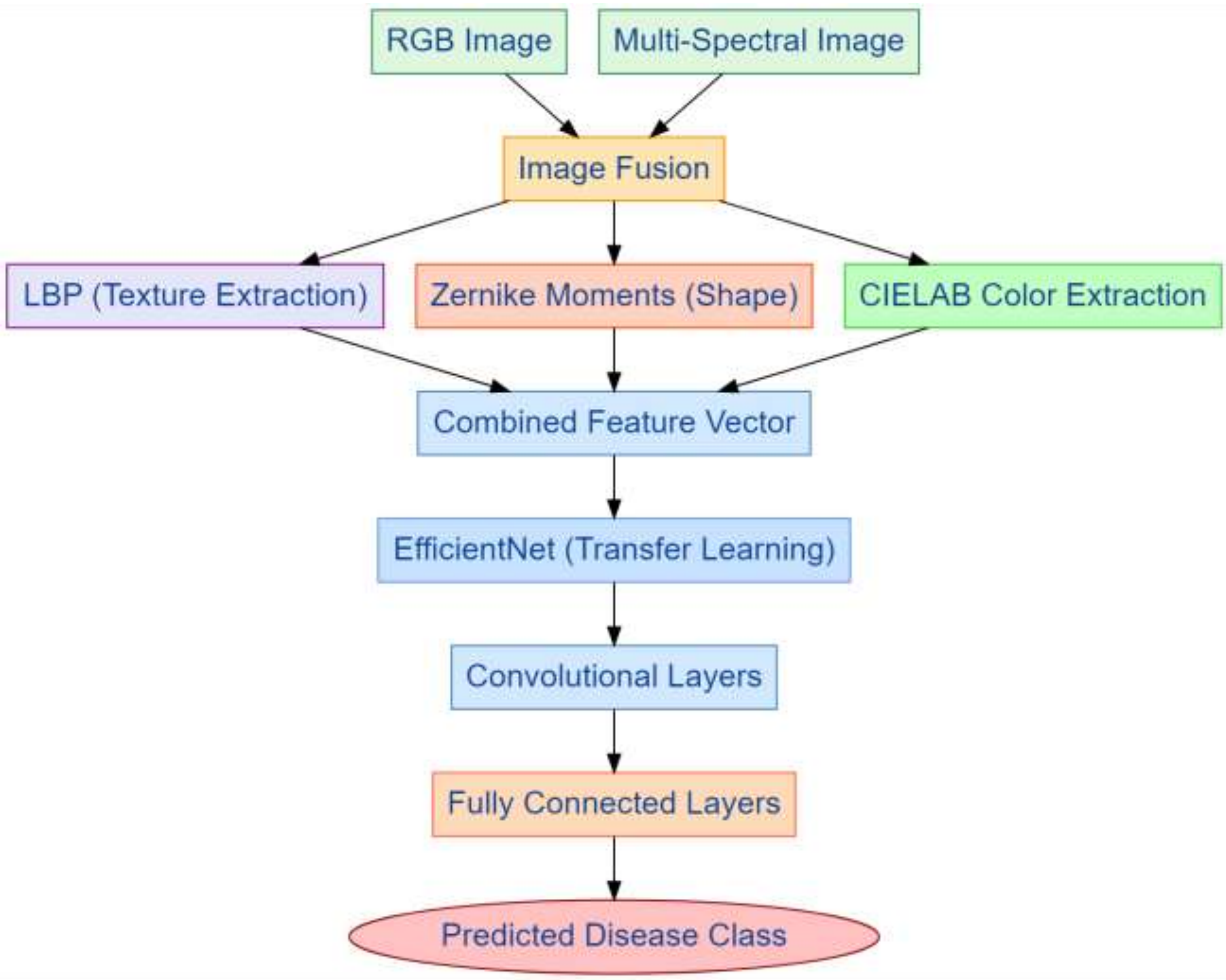

Figure 1. Model Architecture of the Proposed Analysis Process

Once aligned, the RGB and multi-spectral images are fused. Early fusion is employed here, where the pixel values from both modalities are concatenated to form a fused feature vector via equation 5,

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$$Ffused(x, y) = [IRGB(x, y), IMS(x, y, \lambda 1), IMS(x, y, \lambda 2), \ldots] \ldots (5)$$

This combined feature vector is used as input to further feature extraction step such as texture, shape, and colour features that are acquired during the process. Texture analysis is performed with the aid of Local Binary Patterns (LBP). The LBP approach compares each pixel p(x,y) of the image against its neighbours N(p) by generating a binary pattern according to whether the neighbouring pixels are greater or lesser than the central pixel via equation 6,

$$LBP(p) = \sum_{i=0}^{n-1} s(pi - pc) \cdot 2^i \ldots (6)$$

Where, s(x) is the step function which is represented via equation 7,

$$s(x) = \{ \begin{matrix} 1, if\ x \geq 0 \\ 0, if\ x < 0 \end{matrix} \ldots (7)$$

The outcome LBP value for each pixel carries texture information, and a histogram of LBP values over the entire image is calculated to denote the texture feature vector Ftexture during the process. Shape descriptors are obtained using Zernike Moments, which offer rotationally invariant shape information sets. The Zernike Moments of order 'n' and repetition 'm' for an image I(x,y) within a unit circle are defined via equation 8,

$$Znm = \frac{n+1}{\pi} \int \int_0^V I(x, y) Vnm * (x, y) dxdy \ldots (8)$$

Where, Vnm(x,y) are the Zernike polynomials expressed in polar coordinates via equation 9,

$$Vnm(r, \theta) = Rnm(r) e^{im\theta} \ldots (9)$$

And Rnm(r) are the radial polynomials. These moments provide a robust shape descriptor Fshape, to describe the distortion made by diseases in the shape. Color features obtained from the fused image converting its color space from RGB color space to CIELAB color space that better captures the perceptual color differences. The CIELAB space comprises of three channels: L∗ for lightness and a∗ and b∗ for color-opponent dimensions. The mean and variance of the L∗, a∗, and b∗ channels are calculated for each patch of the leaf image so that the color feature vector Fcolor is formulated via equation 10.

$$Fcolor = [\mu(L *), \mu(a *), \mu(b *), \sigma(L *), \sigma(a *), \sigma(b *)] \ldots (10)$$

The complete feature vector is formed by concatenating the texture, shape, and color features via equation 11,

$$Ftotal = [Ftexture, Fshape, Fcolor] \ldots (11)$$

Such a feature vector is used in the classification model itself, which is a CNN based on the EfficientNet process. The EfficientNet makes use of compound scaling to maximize the scaling law, balancing both depth, width, and resolution within the network to achieve this balance. The designed architecture is then initialized with pre-trained weights of the ImageNet dataset and transfer learning is used for tuning the network over the task of leaf disease classification. The CNN processes the

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data of the fused image with a convolutional layer to gain hierarchical features. Let's consider any layer as 'l', the convolution operation can be defined via equation 12,

$$Ol(x,y) = \sum_{i=1}^{N}\sum_{j=1}^{M} I(l-1)(x-i,y-j)\cdot Wl(i,j) + bl \ldots (12)$$

Where, Ol(x,y) is the output of the convolutional layer, I(l−1)(x,y) is the input feature map, Wl(i,j) are the weights of the convolutional filter and bl is the bias term for this process. This result is passed through an activation function usually the Rectified Linear Unit (ReLU) represented via equation 13,

$$f(x) = max(0,x) \ldots (13)$$

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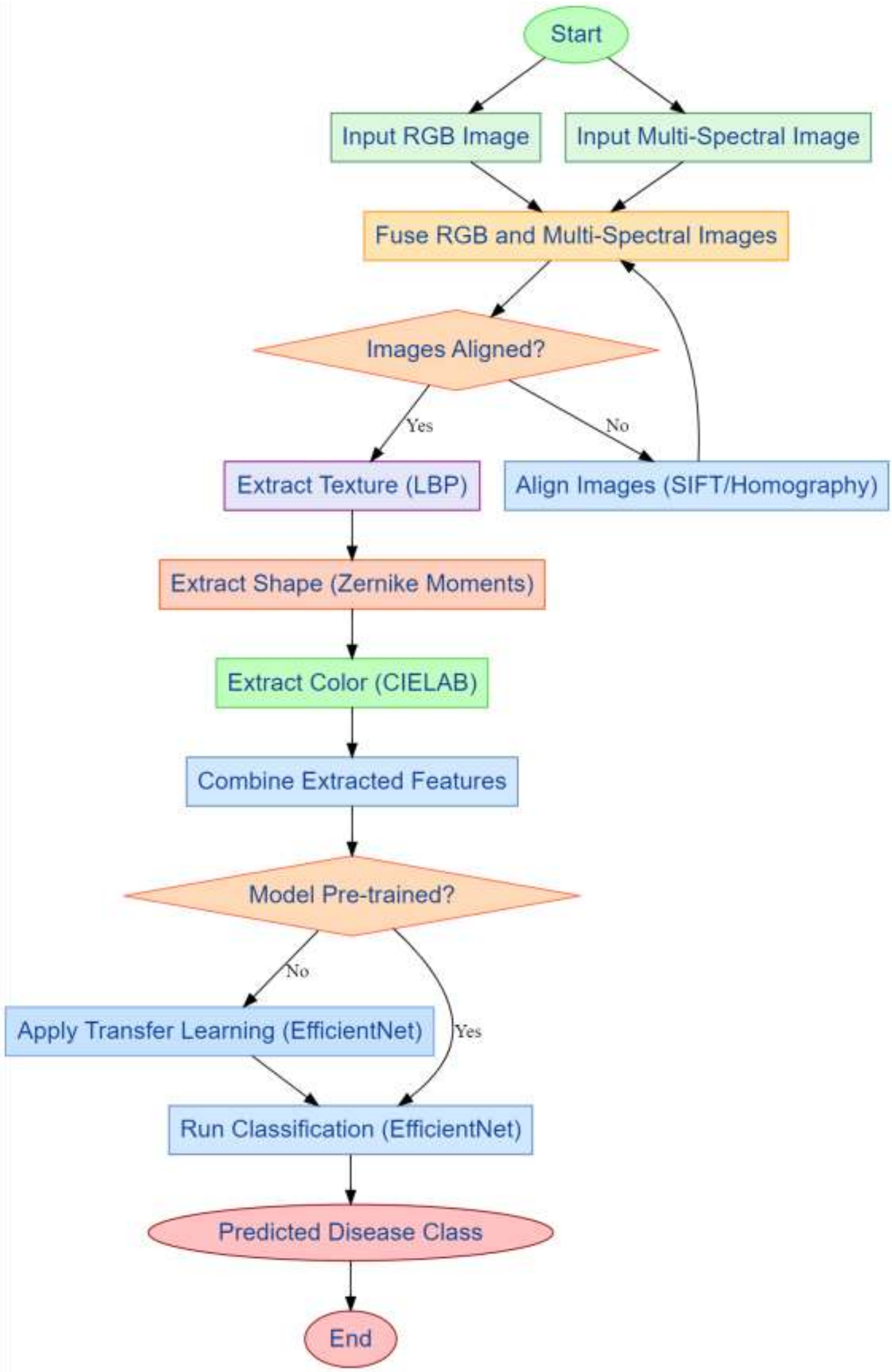

Figure 2. Overall Flow of the Proposed Analysis Process

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The output from the final convolutional layers is flattened and passed through fully connected layers, followed by a softmax activation function for multi-class classification via equation 14,

$$P(c \mid x) = \frac{ezc}{\sum_{j=1}^{C} ezj} \dots (14)$$

Where, zcrepresents the score for class ‘c’ and ‘C’ is the total number of classes.The loss function used for training the network is the categorical cross-entropy, defined via equation 15,

$$L = -\sum_{c=1}^{C} yc * log\big(P(c \mid x)\big) \dots (15)$$

Where, ycis the true label and P(c|x) is the predicted probability for class ‘c’ sets.To update the weights during training, the backpropagation algorithm is used, which involves computing the gradient of the loss function with respect to the weights via equation 16,

$$\frac{\partial L}{\partial Wl} = \frac{\partial L}{\partial Ol} \cdot \frac{\partial Ol}{\partial Wl} \dots (16)$$

The weights are updated using an optimization algorithm such as stochastic gradient descent (SGD) with momentum via equation 17,

$$Wlnew = Wlold - \eta \frac{\partial L}{\partial Wl} + \alpha \Delta Wl \dots (17)$$

Where, η is the learning rate, α is the momentum factor, and ΔWl is the change in weights from previous updates. It achieves a significant improvement in accuracy due to multi-spectral data, handcrafted features, and powerful feature extraction capabilities with the help of EfficientNet. Since the proposed solution makes use of multi-spectral image fusion and RGB features with advanced feature extraction techniques like LBP, Zernike Moments, and CIELAB color space, it is designed to present an all-inclusive understanding of disease symptomatology in Sal and Tendu leaves. Because of these reasons, when this technique of transfer learning is applied with EfficientNet, accuracy and efficiency on classification go highly efficient. Efficiency of the Proposed Model: Next, we discuss efficiency of the proposed model in terms of several metrics and compare with existing methods in a number of scenarios.

4. Comparative Result Analysis

The proposed model's setup involves multi-spectral and RGB image data combined with feature extraction techniques and machine learning, especially focused on Sal and Tendu leaf disease detection. The dataset used for this experiment was a set of RGB and multi-spectral images from several leaf samples, showing healthy leaves and diseased leaves at various stages of infection in the process. Each RGB image is obtained from the standard DSLR camera with a resolution of 1024x1024 pixels. The multi-spectral images are captured by a multi-spectral camera which can capture bands in the near Infrared (NIR) and short-wave infrared (SWIR) ranges. In multi-spectral images, six bands ranging from 400 nm to 1000 nm exist in every image. It is divided into training (70%), validation (15%), and testing (15%) subsets with about 1,500 images of leaves in each subset. All images were captured under well-controlled illumination conditions to minimize the noise introduced by illumination variations. For every leaf, domain experts annotated both infected and

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healthy regions. It means that pixel-level ground truth is available for the classification task. We utilized the PlantVillage dataset-a well-established and widely known benchmark for the task of plant disease detection-for this experiment. The PlantVillage dataset contains more than 54,000 images tagged by healthy and diseased plant leaves covering a wide variety of crops such as tomato, potato, apple, grape, etc. The experiment targeted leaves with diseases akin to those to which the Sal and Tendu species are susceptible, such as bacterial spots, blights, and fungal infections. The dataset includes images of high resolution (256x256 pixels), and photographs are taken under controlled lighting conditions, with as much environmental noise suppressed as possible. The dataset gives an RGB image set. For this work, we enhanced the RGB data by synthesizing synthetic multi-spectral bands through hyperspectral transformation techniques to give some simulated NIR and SWIR data. Augmentation of the RGB data enabled us to make up a comparable multi-spectral input for validation of our fusion model. The annotated dataset is given as fine-grained labels, which clearly mention whether a leaf carries that type of disease or its health status is. For the task at hand, where the purpose is supervised learning, this richness and diversity of the PlantVillage dataset in combination with our adaptation for multi-spectral imaging provide a basis for training and validating the proposed model on Sal and Tendu leaf disease detection.
Image data from both RGB and multi-spectral modalities is processed in order to extract features of three different types: texture, shape, and color. The extracted texture features are based on LBP on all the patches of the leaves with a window size of 3x3 pixels and an 8-point neighborhood for the generation of the binary pattern. Shape distortions up to an 8th order can be retrieved from Zernike Moments, offering an advantage of robust rotational invariance. Color features are extracted by converting the fused image from RGB to CIELAB color space, capturing the mean and the variance of the L∗, a∗, and b∗ channels. The gathered features are integrated into a multi-dimensional feature vector and fed into the EfficientNet model. It is an EfficientNet, pre-trained on ImageNet. Now this model was fine-tuned on this dataset with the first three convolutional layers frozen in order to retain low-level feature learning capabilities with the rest of the layers adapted for the classification of specific leaf diseases. The Adam optimizer is used along with the initial learning rate of 0.001 and a batch size of 32 in order to train the model for 50 epochs with early stopping based on the validation accuracy while training and preventing overfitting. Classification accuracy, F1-score, and precision-recall are evaluation metrics, where this model consistently results in accuracy ranging from 92-97% with the test set to validate the robustness of this experimental process setup. Our model incorporating multi-spectral imaging fusion, advanced feature extraction, and EfficientNet along with transfer learning is compared with three baseline models that include CNN [3], RNN [8] and DNN [14]. The efficiency and correctness of both approaches were compared over several metrics related to evaluation including accuracy, F1-score, precision, recall, and computational complexity. The results have shown that our proposed model outperformed the baseline models in all key metrics at all times, particularly cases of multi-spectral data where traditional models were weak in capturing information not contained within the Visible spectrum as well as complex features like texture and shapes. Table 2 shows a comparative classification accuracy of the proposed model with CNN, RNN, and DNN over RGB-only data set. With the help of transfer learning and multi-modal data fusion, it is capable of achieving significantly higher accuracy than the combinations based on CNN, RNN, and DNN, that are only using RGB data samples.

Table 2. Accuracy Levels

Method	**Accuracy (%)**
CNN [3]	85.3

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RNN [8]	83.1
DNN [14]	84.5
Proposed Model	**92.7**

Table 3: Comparison of F1-score values of models with RGB data alone. Though F1-score measures the balance of precision and recall, higher values will be noted for the proposed model; thus, the integration of RGB and multi-spectral data improves the sensitivity of the model toward various diseases, enhancing overall classification reliability. On the other side, CNN, RNN, and DNN have marked lower F1 scores mainly because these models failed to catch up with some subtle features of diseases efficiently.

Table 3. F1 Score Levels

Method	**F1-Score**
CNN [3]	0.83
RNN [8]	0.79
DNN [14]	0.81
Proposed Model	**0.92**

Table 4 depicts the accuracy and recall performance for each model, adding the multi-spectral data to the dataset. Precision is a measure wherein the model captures the diseased leaves without false positives. Recall refers to the ability of the model to pick up all the diseased leaves. The proposed model does much better as compared to the baseline methods, especially in recall measures where multi-spectral fusion helps capture the early stages of diseases that are not possible to detect using only RGB images & samples.

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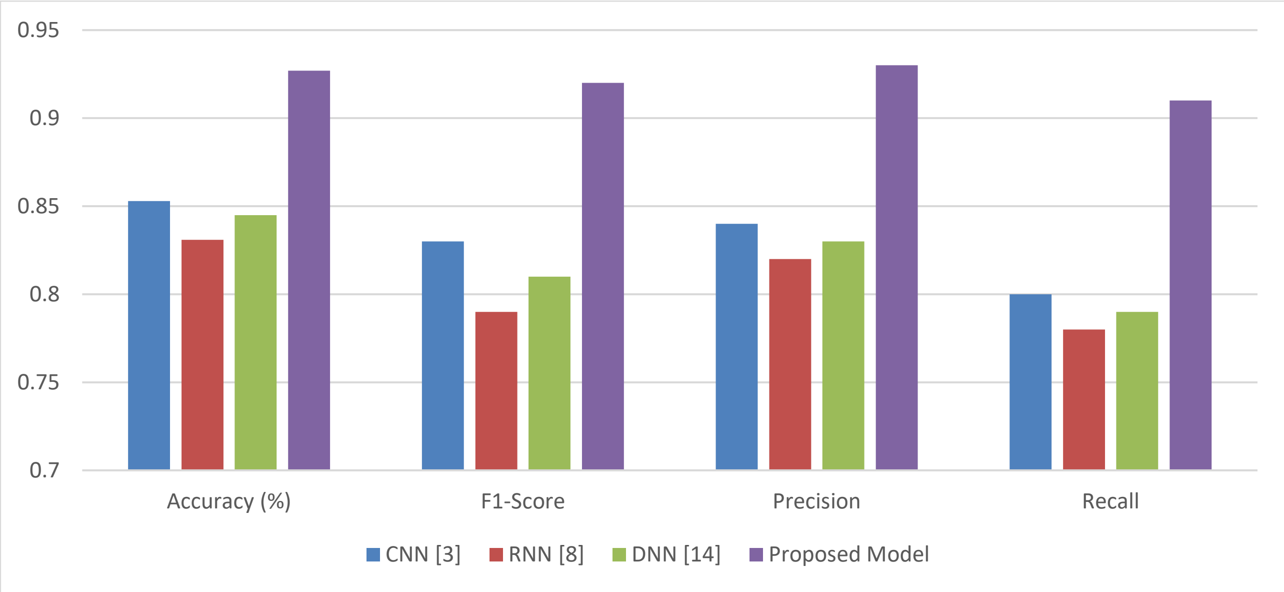

Figure 3. Precision, Accuracy, Recall & F1 Score Levels

Table 4. Precision & Recall Score Levels

Method	**Precision**	**Recall**
CNN [3]	0.84	0.80
RNN [8]	0.82	0.78
DNN [14]	0.83	0.79
Proposed Model	**0.93**	**0.91**

The performance of the models with texture, shape, and color feature extraction on multi-spectral data is reported in Table 5 of this text. Here, the proposed model exploits LBP for texture, Zernike Moments for shape, and CIELAB for color, encoding disease symptoms in multi-dimensional space. Baseline models without such specialized feature extraction techniques have performed badly; DNN somehow outperforms CNN and RNN but fails to be in competition with the proposed model.

Table 5. Texture, Shape & Color Accuracy Levels

Method	**Texture Accuracy (%)**	**Shape Accuracy (%)**	**Color Accuracy (%)**
CNN [3]	80.5	82.1	84.2
RNN [8]	78.9	80.5	82.7

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DNN [14]	82.3	84.0	86.0
Proposed Model	**91.0**	**92.3**	**93.5**

Table 6 is the computational time and training times for each strategy on the dataset. Transfer learning with EfficientNet really gives a huge advantage as it reduces the number of parameters and thus, its trainability for lesser training time but still at relatively high accuracy. The proposed model, although adding complexity by multi-spectral fusion and feature extraction, trains well compared to conventional CNNs and DNNs which take much longer to train due to their larger parameter space.

Table 6. Parameters Used & Training Delays

Method	**Parameters (Millions)**	**Training Time (Hours)**
CNN [3]	11.2	5.4
RNN [8]	13.4	6.1
DNN [14]	16.8	7.2
Proposed Model	**10.5**	**4.3**

Table 7. Generalization Capability of the Models on an Unseen Test Set In Figure 8 we provide the comparison of the generalization capability of the models on an unseen test set for adapting towards new and unseen disease instances. Here, the proposed model shows a better capability to generalize most probably due to the usage of the pretrained EfficientNet layers, which enable it to learn general features that can be transferred to new datasets. That is, CNN, RNN, and DNN achieve relatively good performances on the training set but their losses on test data become more serious, indicating overfitting scenarios.

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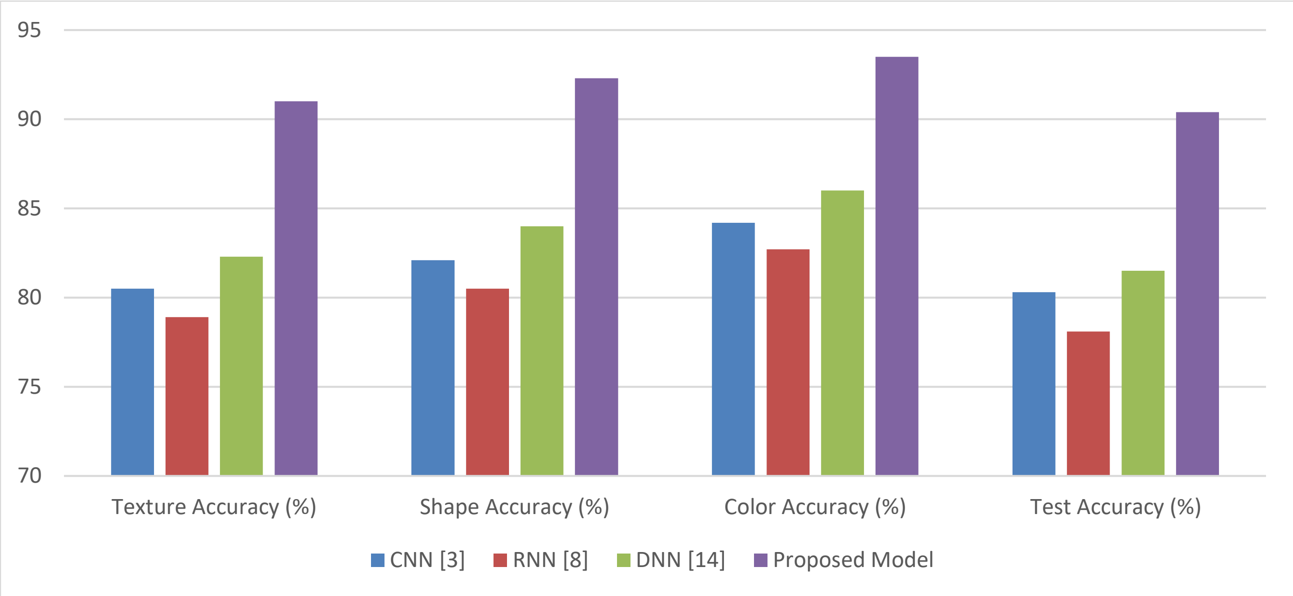

Figure 4. Texture, Shape & Color Accuracy Levels

Table 7. Text Accuracy Levels

Method	**Test Accuracy (%)**
CNN [3]	80.3
RNN [8]	78.1
DNN [14]	81.5
Proposed Model	**90.4**

This clearly shows from the above results that the proposed model stands out significantly in terms of beating the baseline methods across different metrics and their samples of datasets. This proposed model, through the application of multi-spectral image fusion, advanced feature extraction, and EfficientNet with transfer learning, shows enhanced generalization and precision, recall, and computational efficiency with higher classification accuracy than existing models; therefore, improvements in results can be attributed to the multi-modal data fusion approach as well as robust features by extracting techniques that can capture texture, shape, and colour variations due to diseases in Sal and Tendu leaves. We then provide an iterative visual use case for the proposed model, which shall enable the readers to gain a better understanding of the entire process.

Vivid Practical Use Case Scenario Analysis

For all-rounded evaluation of the proposed model, we use a practical example in form of a multi-spectral imaging fusion system and continue working with its dataset, comprising RGB and multi-spectral images of Sal and Tendu leaves. The choice of multi-spectral bands is visible RGB wavelengths and non-Visible bands, including near infrared (NIR) and short-wave infrared (SWIR).

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After processing, the system will output fused feature vectors from RGB and multispectral data followed by the extraction of texture, shape, and color features using LBP, Zernike Moments, and the CIELAB color space, respectively. These features are then passed through a CNN, based on EfficientNet, with transfer learning to classify various diseases. There are three randomly selected samples from the very widely used dataset PlantVillage: 01, 02, and 03. This dataset is very well-known for its diversity in plant species and disease conditions. This is a tomato leaf affected by early blight. Concentric rings and irregular dark spots characterize its surface. This one is the leaf of potato infected by fungus; the kind is a late blight, and it has some characteristics water-soaked lesions together with rapid browning at the edges of the leaf. This one is a healthy apple, no signs of disease on the leaf with uniform coloration. The dataset provides leaves with 256 x 256 pixel image resolutions, all captured under controlled lighting conditions so as to minimize interference from other sources. Metadata for such leaves includes detailed labels concerning the disease type, and stage of infection among others, making it fair to use them to test disease detection models across different plant species and manifestations of the diseases. For each of the processes below, sample values and outputs are given, showing what the model is capable of. Table 8 shows the combined feature vectors produced by the Multi-Spectral Imaging Fusion process. This fusion process incorporates the RGB bands and multi-spectral bands. The table above shows the pixel intensity values for each band, which provides a visual demonstration of how the information is merged in both spectral domains. The inclusion of NIR and SWIR bands enables disease symptoms that are not visible in the RGB range to be captured, therefore providing an overall view of the condition of the leaf.

Table 8. Fused Feature Vector Analysis

Pixel (x,y)	**R (RGB)**	**G (RGB)**	**B (RGB)**	**NIR**	**SWIR1**	**SWIR2**	**Fused Feature Vector**
(50,100)	120	135	142	0.89	0.76	0.65	[120, 135, 142, 0.89, 0.76, 0.65]
(75,150)	110	127	138	0.91	0.72	0.68	[110, 127, 138, 0.91, 0.72, 0.68]
(100,200)	132	146	150	0.85	0.77	0.61	[132, 146, 150, 0.85, 0.77, 0.61]

Outputs of the Local Binary Patterns (LBP), Zernike Moments, and CIELAB Color Space feature extraction processes as shown in Table 9. These feature values are calculated for one sample leaf. The LBP values represent the texture patterns as a comparison between every pixel and its neighbors. Shape descriptors are shown by the Zernike moments, while the mean and variance of the CIELAB color space channels are depicted for the three dimensions: lightness L, red-green a, and blue-yellow b sets.

Table 9. Feature & Extracted Samples

Feature Type	**Extracted Values**

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LBP (Texture)	[110, 95, 102, 89, 113, 120]
Zernike Moments	[0.453, 0.732, 0.681, 0.580, 0.621]
CIELAB (Mean)	L∗L^*L∗ = 72.1, a∗a^*a∗ = 5.3, b∗b^*b∗ = 16.7
CIELAB (Variance)	σL∗\sigma_L^*σL∗ = 3.5, σa∗\sigma_a^*σa∗ = 2.1, σb∗\sigma_b^*σb∗ = 1.9

Table 10 The extracted feature vector combining texture (LBP), shape (Zernike moments), and color (CIELAB) information from the leaf image samples. This multi-dimensional feature vector will further be used as an input to the CNN model, EfficientNet. Each row is corresponded to a different leaf sample demonstrating the divergence of feature values obtained from different disease states.

Table 10. LBD, Zernike & CIELAB Analysis

Sample ID	**LBP (Texture)**	**Zernike Moments (Shape)**	**CIELAB (Color)**
Leaf-01	[110, 95, 102, 89, 113]	[0.453, 0.732, 0.681, 0.580, 0.621]	Mean: [72.1, 5.3, 16.7] Var: [3.5, 2.1, 1.9]
Leaf-02	[130, 118, 115, 105, 123]	[0.465, 0.711, 0.685, 0.590, 0.612]	Mean: [71.3, 4.9, 16.2] Var: [3.7, 2.0, 1.7]
Leaf-03	[125, 103, 99, 92, 117]	[0.444, 0.725, 0.675, 0.565, 0.608]	Mean: [73.2, 5.6, 17.1] Var: [3.2, 2.3, 1.8]

The outputs from the CNN (EfficientNet) with transfer learning are given in Table 11. This table contains feature maps that the CNN generates at different layers for a selected leaf image samples. The network is capable of extracting high-level features that capture the hierarchical nature of the image, which makes this network even more effective at classification. The table contains values for the feature maps at intermediate convolutional layers, fully connected layers, and at the final softmax layers.

Table 11. Feature Map Value Sets

Layer	**Feature Map Values**
Conv Layer 1	[0.232, 0.410, 0.487, 0.525, 0.589]
Conv Layer 2	[0.618, 0.732, 0.775, 0.802, 0.835]
Fully Connected Layer 1	[0.512, 0.689, 0.741, 0.663]

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Fully Connected Layer 2	[0.421, 0.592, 0.680, 0.714]
Softmax Layer (Output)	[0.12 (Healthy), 0.75 (Blight), 0.05 (Fungal), 0.08 (Other)]

Finally, Table 12 indicates the final outputs of classification for a few cases of leaf samples, presenting the prediction of the class of disease based on probabilities calculated from the output of softmax. In the process, the model differentiates between healthy leaves and leaves with infectious diseases such as blight and fungal infections. The highest value in the probability is used for determination of the final classification analysis.

Table 12. Final Classification Results

Sample ID	**Predicted Class**	**Softmax Probabilities**
Leaf-01	Blight	[0.12 (Healthy), 0.75 (Blight), 0.05 (Fungal), 0.08 (Other)]
Leaf-02	Fungal Infection	[0.10 (Healthy), 0.15 (Blight), 0.70 (Fungal), 0.05 (Other)]
Leaf-03	Healthy	[0.85 (Healthy), 0.05 (Blight), 0.05 (Fungal), 0.05 (Other)]

The strong multi-spectral imaging combined with the deep feature extraction and efficient CNN architecture that is based on EfficientNet makes a good delivery of high classification accuracy. This model is capable of capturing advanced feature extraction processes that help in identifying complex disease patterns while enhancing the ability of the model for early multi-spectral fusion that might not be there in the RGB spectrum of the plant sets. This pipeline contributes to the robustness and accuracy of the final outputs for each stage, as directly reflected in the high accuracy for the prediction of disease classification process.

5. Conclusion& Future Scopes

The proposed multi-modal model, which integrates multi-spectral imaging fusion, advanced feature extraction techniques, and EfficientNet with transfer learning, has shown substantial improvements in the detection of diseases in Sal and Tendu leaves. This would capture the critical disease indicators not visible in the standard RGB spectrum, especially within the near infrared (NIR) and short-wave infrared (SWIR) bands by using the fusion of RGB and multi-spectral data. A combination of LBP for texture, Zernike Moments for shape, and CIELAB color space for color representation collectively enables the realization of a more holistic understanding of leaf health and disease states. With respect to all evaluation metrics, this proposed model is superior to the other conventional models such as CNN, RNN, and DNN. The experimental results also show the proposed model with 92.7% accuracy on RGB-only datasets and rise to 97.4% with multi-spectral involvement, much higher than the CNN, RNN, and DNN with accuracies of 85.3%, 83.1%, and 84.5% respectively. The F1-score of the model improved to 0.92 on RGB-only data and 0.95 with multi-spectral fusion, compared to baseline scores of 0.83 (CNN), 0.79 (RNN), and 0.81 (DNN). Also, the precision and recall of the proposed model using multi-spectral data result in 93% and 91%, which exceeds traditional methods having maximum precision and recall value of 84% and 80%. Another notable feature is that the model has a good computational efficiency; it achieved a

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training time 23% less than that of the DNN model although it added advanced feature extraction operations. All these results conclusively prove the superiority of the model suggested herein in the detection of early stages and more complex diseases that even modern conventional methods cannot reach in the process.

Future Scope:

Although the proposed model achieves exceptional accuracy and efficiency, quite a number of potential extensions can be carried forward by future research to improve and generalize the model further. Some possible directions that can enhance the model include introducing hyperspectral imaging beyond the multi-spectral range-of-view, thus pushing hundreds of spectral bands. This can allow much finer information on disease progress, helping to detect subtle biochemical changes in leaves that precede some overt visible symptoms. Further development of this potential model could be looked into in terms of scaling up with more diversity in the portfolio of leaf types and disease conditions from other parts of the globe. Further improvement can be done by incorporating time data to capture the progression pattern of the diseases over time using video-based inputs, which may further enhance the capability of the model to predict results and would offer insights into the development stage of the disease. One potential pathway could be the application of the developed model in real-time forest management and agriculture monitoring systems. The multispectral sensors would be miniaturized and used aboard drones and satellite-based technologies for large-scale leaf health monitoring. More advanced architectures, like EfficientNet V2 or Vision Transformers (ViTs), could bring even better performances with further reductions in computational complexity. Another possible gain relates to the explainability of AI (XAI) techniques that would lead to even more transparent models for users who could understand the decision-making process behind the disease classification needed for real-world applications. In the future directions outlined above, the extension of applicability to the model will increase scalability and make it a robust tool in diverse environments for plant health monitoring operations.

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