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HYBRID FEATURE FUSION MODEL SELECTION FOR COFFEE LEAF DISEASE CLASSIFICATION

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Abstract: A one of a kind hybrid feature combination technique for precise coffee leaf disease determination is proposed in this exploration to answer the pressing interest for ideal infectious prevention in farming. Customary methodologies normally lose accuracy due to natural and picture vacillations, requiring a further developed arrangement. The recommended technique gathers visual attributes utilizing MobileNetV3, Swin Transformer, Xception, and DenseNet201 models. Swin Transformer accumulates undeniable level elements, MobileNetV3 nearby highlights, and Xception and DenseNet201 give additional experiences. These recovered qualities are consolidated before classification utilizing early and late combination organizations. This study explores the utilization of Xception and DenseNet201 models to further develop execution to 90% or better. MobileNetV3 and Swin Transformer acquired 84% accuracy in the base paper. This methodology might further develop coffee crop disease classification accuracy by combining a few models and combination draws near, empowering better infectious prevention and yield quality confirmation.

Index Terms: Coffee leaf disease classification, feature fusion, hybrid model.

1. INTRODUCTION

Agriculture represents more than 4% of the worldwide Gross domestic product [1]. Its financial impact goes past numbers, particularly in Africa and Asia's Vietnam, Indonesia, and Ethiopia. Agriculture lessens destitution, raise pay, and make occupations. Robusta coffee beans rule these areas' agrarian merchandise. From ranch to showcase, Robusta coffee trees are tormented by sicknesses including leaf rust and red insect parasites, which might be horrendous.

These illnesses undermine horticultural result, causing 75% losses in outrageous cases and north of two billion US dollars in yearly losses [2,43]. Conventional illness discovery requires manual examinations by experienced laborers, which is strenuous and tedious, particularly on enormous estates of a few hundred hectares. Given the greatness of coffee creation and the need of brief infectious prevention, successful and exact robotized location advancements are required.

As of late, PC vision and ML have shown guarantee for horticultural infection finding [3], [4]. Starting endeavors utilized computerized cameras to catch plant leaf pictures, then ML strategies like k-means

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clustering and outspread premise capability organizations to distinguish sicknesses [3], [4]. These strategies required manual element extraction, which was tedious and hindered adaptability and speculation [5], [6], [7].

Deep learning methods have arisen to naturally extricate huge qualities from raw picture information [6], [8], [9]. Plant leaf infection datasets have expanded [10], [11], [12], [13], making deep learning models for sickness characterization more straightforward to make and test [14], [15], [44] [16]. Convolutional Neural Networks (CNNs) are a foundation of deep learning models since they naturally separate various leveled data from pictures [14], [15], [16].

CNN models pretrained on ImageNet like VGG, ResNet, DenseNet, EfficientNet, and MobileNet characterize plant leaf infections well [14], [15], [16], [17], [18]. Imaginative techniques like CNN-consideration component mix have improved characterization accuracy [20], [21]. Notwithstanding these advances, unconditioned photos in genuine conditions stay troublesome [17,45].

Unmodified settings need critical variety contrasts between picture objects like leaves, grass, and trees in certifiable photos. Customary CNNs that utilization pixel-level differences might battle to classify such pictures [17]. Each CNN spine model concentrates includes in an unexpected way, zeroing in on various channels or picture aspects.

To conquer these issues, highlight combination is a reasonable technique for coordinating CNN include maps into a more complete portrayal [23]. Link and other combination calculations defeat network limitations, further developing characterization and bringing down figuring costs [24]. Gathering approaches can join choice level results from a huge number to further develop characterization execution.

This exploration examines how crossover include combination could further develop espresso leaf illness identification accuracy and robustness. The proposed arrangement utilizes deep learning models and combination methods to address genuine picture conditions and further develop coffee plantation disease management.

2. LITERATURE SURVEY

Agriculture, the foundation of the worldwide economy, has a few issues, including plant infection recognition and treatment. Agriculture's commitments to the worldwide GDP exhibit its financial significance [1]. Agribusiness is urgent to destitution mitigation, income producing, and work advancement in Vietnam, Indonesia, and Ethiopia [1].

Coffee production is significant in horticulture, particularly in Robusta-developing nations. Diseases like leaf decay and red insect vermin undermine espresso homesteads' efficiency and maintainability [2]. In extreme conditions, these ailments can decrease espresso harvests by 75% and cost the business billions [2].

Disease recognition in agribusiness has customarily relied upon actual examinations by experienced staff, which is difficult and tedious, particularly on a few hundred-hectare ranches [2]. Human blunder and shortcoming describe this technique. Accordingly, there is a rising need to utilize innovation to make

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computerized location frameworks that accelerate and upgrade precision.

PC vision and ML have empowered progressive horticultural arrangements like sickness determination [3], [4]. Computerized cameras were utilized to catch plant leaf pictures for robotized illness analysis, trailed by ML strategies including k-implies grouping and outspread premise capability networks [3], [4]. These methodologies were promising, however manual component extraction restricted adaptability and consensus [5], [6], [7].

Deep learning calculations can consequently extricate highlights from crude picture information to avoid these limitations [6], [8], [9]. Datasets on plant leaf infections have helped plan and test deep learning models for sickness classification [10], [11], [12], [13]. Convolutional Neural Networks (CNNs) are famous deep learning designs since they consequently separate progressive highlights from pictures [14], [15], [16].

CNN models pretrained on ImageNet, like VGG, ResNet, DenseNet, EfficientNet, and MobileNet, have arranged plant leaf illnesses well [14], [15], [16], [17], [18]. Advancements like blending CNNs with consideration processes have improved arrangement exactness [20], [21]. Regardless of these advances, unconditioned photos in genuine conditions stay troublesome [17].

Unmodified settings need huge variety contrasts between visual items like leaves, grass, and trees [17]. Conventional CNNs that utilization pixel-level differences might battle to sort such pictures [17]. Each CNN spine model concentrates includes in an unexpected way, zeroing in on various channels or picture aspects.

To conquer these issues, include combination is a practical technique for incorporating CNN highlight maps into a more complete portrayal [23]. Connection and other combination calculations beat network limitations, further developing arrangement and bringing down processing costs [24]. Outfit approaches can consolidate choice level results from a huge number to further develop grouping execution.

This exploration examines how crossover include combination could further develop coffee leaf disease detection accuracy and robustness. The recommended arrangement utilizes profound learning models and combination procedures to address true picture conditions and further develop coffee plantation disease management.

3. METHODOLOGY

a) Proposed Work:

A mixture highlight combination technique for coffee leaf disease finding utilizing refined deeplearning models like MobileNetV3[29], Swin Transformer, and variational autoencoder is recommended. MobileNetV3 separates neighborhood highlights, while Swin Transformer extricates significant level qualities. VAE adds dormant data to the element space by learning inert portrayals. The framework flawlessly coordinates differed model qualities utilizing early and late combination draws near. Synergistically incorporating these models' capacities could further develop coffee leaf disease recognizable proof accuracy. The framework can get unpretentious examples and changes in coffee leaf pictures utilizing

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this exhaustive combination strategy, bringing about more accurate disease diagnosis.

b) System Architecture:

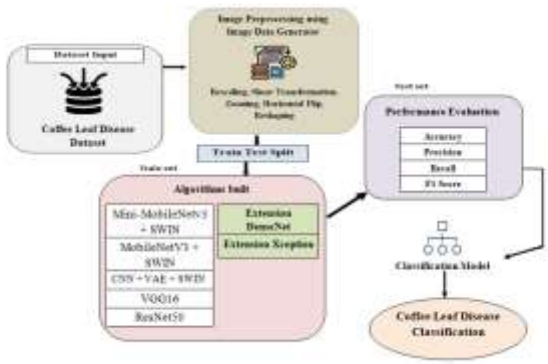

Fig 1 Proposed Architecture

A few significant parts make up the coffee leaf disease order framework design. Beginning with a wide arrangement of coffee leaf photographs from the Coffee Leaf Disease Dataset, preparing and assessment start. To further develop preparing information versatility and changeability, a Picture Information Generator permits picture handling strategies including rescaling, shear change, zooming, level flip, and reshaping.

Subsequent to preprocessing, the dataset is isolated into preparing and testing. The preparation set trains grouping strategies as Smaller than usual MobileNetV3+SWIN[29], MobileNetV3+SWIN, CNN+VAE+SWIN, VGG16[14,48], and ResNet50, which utilize different designs and element extraction abilities. These calculations figure out how to distinguish espresso leaf infection designs.

The prepared models are then tried on the test set utilizing accuracy, precision, recall, and F1 score. These estimations show how well the models characterize espresso leaf infections. At long last, the order model is utilized to naturally distinguish and analyze coffee leaf diseases utilizing leaf photographs. This framework configuration assists ranchers with controlling coffee leaf diseases and guarantee crop quality by ordering them precisely.

c) Dataset Collection:

A few significant parts make up the espresso leaf illness order framework engineering. Beginning with a wide arrangement of espresso leaf photographs from the Coffee Leaf Disease Dataset, preparing and assessment start. To further develop preparing information flexibility and changeability, a Picture Information Generator permits picture handling procedures including rescaling, shear change, zooming, level flip, and reshaping.

Subsequent to preprocessing, the dataset is isolated into preparing and testing. The preparation set trains characterization strategies as Mini-MobileNetV3+SWIN[29], MobileNetV3+SWIN, CNN+VAE+SWIN, VGG16[14,49], and ResNet50, which utilize different structures and element extraction capacities. These calculations figure out how to recognize coffee leaf disease designs.

The prepared models are then tried on the test set utilizing accuracy, precision, recall, and F1 score. These estimations show how well the models characterize espresso leaf sicknesses. At long last, the grouping model is utilized to consequently recognize and analyze coffee leaf diseases utilizing leaf photographs. This framework configuration assists ranchers with controlling coffee leaf disease and guarantee crop quality by grouping them precisely.

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Fig 2 Sample Dataset

d) Image Processing:

ImageDataGenerator

Image preprocessing is fundamental for ML model information readiness. We change the dataset utilizing ImageDataGenerator to build its versatility and fluctuation.

Guarantee dataset input aspects are steady by rescaling photographs to a uniform size. Standardization helps model preparation union.

Shear Change: Moving one picture pivot causes controlled contortion. This technique mimics genuine vacillations like perspective changes, working on model speculation.

Zooming: Amplifying or bringing down the image size gives the model more information perspectives. This increase approach catches leaf primary elements and changes.

Level flipping mirrors the image upward, adding evenly flipped photographs to the assortment. This change helps pivot invariant learning and dataset size.

Reshaping: Reshaping the image guarantees input aspects match the model's measures. This step is fundamental for neural network design similarity.

These image processing strategies give assortment to the dataset while holding its honesty. The model learns hearty elements and sums up to obscure information better with this expansion strategy.

e) Algorithms:

Mini-MobileNetV3 + SWIN: The lightweight plan of Mini-MobileNetV3 and the vigorous component extraction capacities of SWIN Transformer are utilized to proficiently gather nearby and undeniable level highlights from input photographs. Smaller than normal MobileNetV3[29,50] processes rapidly and lightweightly, though SWIN Transformer works on lengthy reach conditions and context oriented data.

MobileNetV3 + SWIN: This procedure utilizes MobileNetV3's proficient component extraction and SWIN Transformer's consideration calculations to catch neighborhood and worldwide qualities. The depthwise distinguishable convolutions of MobileNetV3 offer lightweight handling, while SWIN Transformer upholds powerful component portrayal learning.

CNN + VAE + SWIN: This calculation utilizes CNNs, VAEs, and SWIN Transformers. CNNs extricate progressive highlights from input pictures, though VAE creates inert portrayals for more minimal and significant element portrayals. SWIN Transformer catches long-range conditions and spatial collaborations to further develop portrayals.

VGG16: This exemplary deep convolutional neural network engineering separates includes effectively and actually. VGG16[14] gathers complex examples and progressive qualities from input pictures with a profound pile of convolutional layers, making it ideal for picture order.

ResNet50: This ResNet variety is known for its deep residual learning structure. ResNet50[15,52] takes care of the disappearing gradient issue with skip associations, empowering deep neural network preparing. This plan is utilized for picture arrangement, particularly coffee leaf disease analysis, since it catches nuanced subtleties.

4. EXPERIMENTAL RESULTS

Accuracy: The model's accuracy is the percentage of true predictions at a grouping position. Mathematically, this can be stated as:

Accuracy = TP + TN TP + TN + FP + FN.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

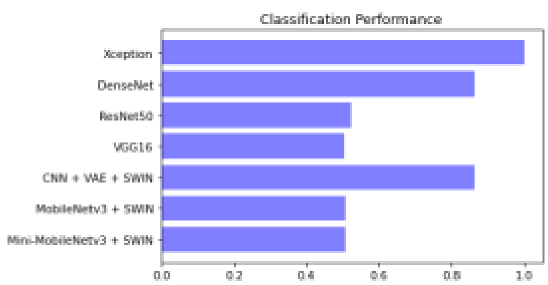

Fig 3 Accuracy Comparison Graphs

F1-Score: The F1 score captures both false positives and false negatives, making it a harmonized precision and validation technique for unbalanced data sets.

$$\textbf{F1 Score} = \frac{2}{\left(\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}\right)}$$

$$\textbf{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

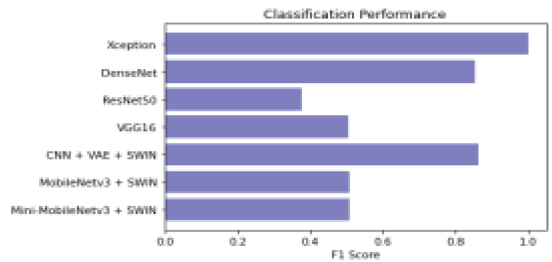

Fig 4 F1 Score Comparison Graphs

Precision: Precision quantifies the percentage of certain events or tests that are well characterized. To attain accuracy, use the formula:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\text{Precision} = \frac{\mathit{True\ Positive}}{\mathit{True\ Positive} + \mathit{False\ Positive}}$$

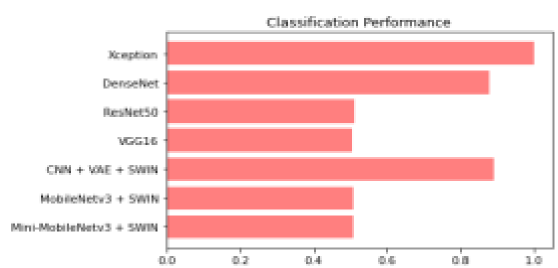

Fig 5 Precision Comparison Graphs

Recall: ML recall measures a model's ability to catch all class occurrences. The model's ability to recognize

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a certain type of event is measured by the percentage of precisely anticipated positive prospects that turn into real earnings.

$$Recall = \frac{TP}{TP + FN}$$

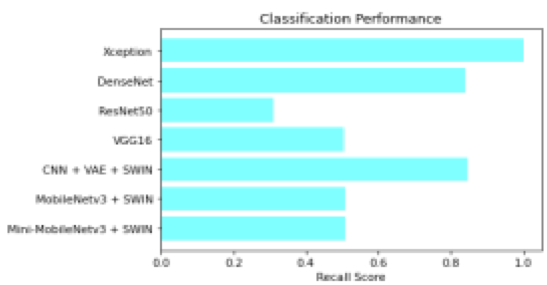

Fig 6 Recall Comparison Graphs

ML Model	Accuracy	Precision	Recall	F1-Score
Mini-MobileNetv3 + SWIN	0.507	0.507	0.507	0.507
MobileNetv3 + SWIN	0.507	0.507	0.507	0.507
CNN + VAE + SWIN	0.863	0.891	0.847	0.862
VGG16	0.505	0.506	0.506	0.506
ResNet50	0.522	0.510	0.509	0.376
Extension DenseNet	**0.861**	**0.879**	**0.841**	**0.853**
Extension Xception	**1.000**	**1.000**	**1.000**	**1.000**

Fig 7 Performance Evaluation Table

Fig 8 Home Page

Fig 9 Registration Page

Fig 10 Login Page

Fig 11 Upload Input Image

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Fig 12 Predicted Results

Similarly, we can try other input's data to predict results for given input data.

5. CONCLUSION

At long last, the hybrid feature fusion strategy utilizing MobileNetV3 and Swin Transformer models for mechanized coffee leaf disease finding is promising. The recommended method further develops disease identification exactness and dependability by utilizing MobileNetV3[29,51]'s productive component extraction and Swin Transformer's presentation upgrading attributes. Our Robusta Coffee Leaf (RoCoLe) dataset appraisal shows further developed execution contrasted with existing methodologies, with 84.29% testing accuracy.

Later on, hybrid feature fusion utilizing equipment gas pedals like Intel Jetson Nano could make the recognition framework pertinent to remote cultivating areas. Likewise, applying the cross breed highlight combination technique to extra genuine world datasets will further develop sickness determination in different settings. Dissecting plant leaf illness levels further develops the board and infectious prevention.

In later turns of events, combining dee learning models like Xception and DenseNet[16] for coffee leaf disease classification and a Flask-based front end for testing and approval could further develop framework ease of use and usefulness. The recommended technique robotizes coffee leaf disease finding, further developing sickness the board and harvest security in coffee farms.

6. FUTURE SCOPE

The hybrid feature fusion technique for coffee leaf disease conclusion has a few exploration and application prospects. Utilizing equipment gas pedals like the Intel Jetson Nano is urgent to disseminating the location framework to far off rural regions. This arrangement lets farmers, particularly those in country places without cutting edge innovation, utilize versatile stuff for sickness checking and the board, working on rural result and supportability.

Extending hybrid feature fusion past the RoCoLe dataset to extra genuine world datasets is essential for affirming its handiness across fluctuated espresso leaf infection circumstances. This extended dataset examination works on the model's responsiveness to climatic and illness conditions and guarantees its flexibility and reliability in agricultural settings.

Moreover, point by point plant leaf disease level examinations may significantly further develop infection the board strategies. By understanding illness seriousness and improvement, partners might make

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designated activities to diminish crop losses and augment disease the executives efficacy.

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Dataset Link :

Train :
https://www.kaggle.com/datasets/jumenta/rocole-train

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Test: https://www.kaggle.com/datasets/jumenta/rocole-test

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