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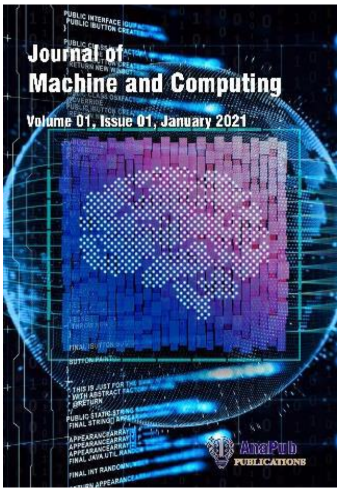

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Sugarcane Leaf Disease Prediction Using Wavelet Prompt-tuned Muti-Task Taxonomic Transformer with Hierarchical Auto-Associative Polynomial Network

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Abstract - Accurate modeling of sugarcane leaf diseases poses several challenges, including the need for large and diverse datasets, difficulty in differentiating between visually similar disease symptoms, and the adverse effects of environmental variability on model accuracy. Additionally, real-time prediction remains computationally intensive and often lacks generalizability across different crop types and geographical regions. To address these limitations, this paper proposes a novel framework—Wavelet Prompt-Tuned Multi-Task Taxonomic Transformer with Hierarchical Auto-Associative Polynomial Network (WATT-Net)—applied to the Sugarcane Leaf Image Dataset for effective disease prediction. Image pre-processing is enhanced through Discrete Wavelet Transformation combined with Pre-Gaussian Filtering (DWT-PGF) to reduce noise and blur, thereby improving image clarity. Region deviation analysis is employed to localize disease-affected areas, followed by Prompt-Tuned Multi-Task Taxonomic Transformer (PTMT)-based segmentation, which ensures precise boundary delineation. The new architecture (proposed PTMT architecture) does not manually engineer prompts but instead, they are learnt using a data-driven approach during training. The learned prompts represent task specific contextual priors and are dynamically adjusted to perform multi-tasks and their segmentation and classification better via formulating attention mechanism of the transformer.The Scale-Aware Hierarchical Auto-Associative Polynomial Network (SA-HAAP-Net) further strengthens the framework by extracting discriminative features for accurate classification. Disease region identification is refined using the Walk-Spread Algorithm (WSA), which contributes to higher detection accuracy and reduced error rates. Experimental results using Python-based implementation demonstrate superior performance, achieving 99.9% accuracy and 99.8% sensitivity, significantly outperforming existing models. The proposed WATT-Net approach offers a robust and scalable solution for real-time sugarcane leaf disease detection, with strong potential for broader agricultural applications.

Keywords - Crop leaf disease, Discrete Wavelet Transformation, Prompt-Tuned Multi-Task Taxonomic Transformer, Sugarcane Leaf Image Dataset, Walk-Spread Algorithm.

I. INTRODUCTION

Agriculture plays a key role in nurturing the world's growing populace. In order to meet the increasing demand for food, agricultural production needs to be boosted while loss needs to be minimized. Precise predictions of crop growth and analysis are crucial to contemporary agriculture, and machine learning is increasingly becoming a powerful means to achieve these ends [1].Precision farming, also known as "smart farming," employs cutting-edge technology in order to drive agricultural production upwards and reduce wastage [2]. Such a strategy is aimed at boosting agricultural productivity in a way that conserves very important resources such as energy, water, and fertilizer. Agriculture is taken to be the backbone of any nation since agricultural and industrial revolution took place together. Crops are essential to human survival, and crop health is essential to food security and economic stability [3]. One of the most urgent issues facing the world today is food insecurity, which is largely caused by crop diseases. Plant diseases not only endanger the world's food supply but also have a major detrimental effect on daily living and the economy. Crop leaf growth and condition are important markers of the general health of the plant [4]. Important information regarding a variety of plant illnesses can be found in the visual signals on leaves. Vegetable crops, such as potatoes, tomatoes, rice, and peppers, are very susceptible to a variety of diseases, resulting in significant financial losses each year. There are two types of blight, a prevalent and harmful illness: early blight, which is brought on by a fungus, and late blight, which is brought on by certain bacteria. Waste and monetary loss can be avoided with early identification and efficient treatment of these illnesses [5][6]. Given that there will likely be more than 9 billion people on the planet in the next 25 years, food production needs to rise by 70% to keep up with demand. Crop diseases remain a serious concern, especially in rural and agricultural areas. Diseases affecting potatoes are especially worrying because they are the most consumed vegetable in the world, but illnesses affecting tomatoes and peppers also pose significant dangers [7].

Sugarcanes are among the major crops that have a significant role because they are highly used in production of sugar, biofuel and alcohol. Regrettably, various leaf diseases, such as red rot, smut, leaf scald, rust, and mosaic are highly susceptible to sugarcane crops[8].The diseases usually start by causing small spots on the leaves and eventually affect the health of the plants and their productivity. Conventional manual inspection is tedious, time consuming and not always accurate. Consequently, automated intelligent disease prediction systems are urgently needed to assist in precision agriculture[9]. Recent progress in machine learning (ML) and deep learning (DL) has made automated crop monitoring more practical and effective. Such ML models as Support Vector Machines (SVM), Random Forests, and K-Nearest Neighbors (KNN) have been extensively applied to the classification of healthy and diseased leaves based on shape, color, and texture features[10] [11]. Nevertheless, these models are vulnerable on the manual feature extraction and they tend to perform poorly on large datasets that are high dimensional. These shortcomings have been addressed by proposing deep learning architectures, including Convolutional Neural Networks (CNNs)[12], Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks. Such models automatically learn features on raw images, and they provide improved accuracy on complex classification tasks. Deep learning plays a key role in smart farming by combining sophisticated algorithms, tools, and techniques. Complex agricultural tasks including feature extraction, data processing, pattern recognition, and image classification are addressed by machine learning [13].

Wavelet transforms formed potent tools in agricultural image analysis, which may be applied in extracting spatial and frequency characteristics of leaf images. In contrast to pure filters or edge detectors, wavelet transforms enable multi-resolution analysis of the disease patterns. In the case of leaf disease detection, preprocessing using the wavelet transform helps to boost high-resolution textures and color disparity which can be a result of an early infection. Wavelet features are useful in making deep models more sensitive to detecting subtle changes in diseased leaves [14]. The capability of extracting both spatial and frequency-based features is important in the domain of agricultural image analysis, particularly in applications such as plant disease detection. The wavelet transform is one of the effective approaches which can be used to this end. This is in contrast to some older image processing methods like simple filters or edge detectors which can be thought of as acting on only a single scale. This feature is very useful especially in the detection of symptoms of diseases that have different sizes, intensities and positions[15].

In the wavelet-based preprocessing used in the detection of leaf disease, the preprocessing stage is important in bringing out the visual appearance of the leaf. It reveals fine textures, slight color variations and abnormal patterns that are frequently early signs of disease. The human eye or simple image filters may be not sensitive enough to pick up these symptoms, particularly when the conditions are harsh (e.g. poor lighting) or when symptoms overlap. Wavelet transforms can aid in preserving features and reducing noise by decomposing the image into elements which represent both high-frequency (detail) and low-frequency (structural) information. This leads to cleaner more informative features to downstream machine learning or deep learning models[16].These features extracted by a wavelet when used alongside more complex models like Convolutional Neural Networks (CNNs) or Transformer-based models, greatly improve the sensitivity and accuracy of the model. The models are made more competent in identifying even the slightest variation between the healthy and the diseased areas. This becomes essential to the actual farm work, as timely and correct diagnoses of the diseases may result in timely measures, and thus, minimal losses of crops, and food security[17].

Novelty and contribution

The Novelty and contribution of this paper is given below:

- The Sugarcane Leaf Image Dataset is used by the Wavelet Prompt-Tuned Multi-Task Taxonomic Transformer with Hierarchical Auto-Associative Polynomial Network (WATT-Net) to efficiently address crop leaf disease diagnosis difficulties.
- Through reduction of noise and blurring effects, pre-processing using Discrete Wavelet Transformation and Pre-Gaussian Filtering (DWT-PGF) significantly enhances the clarity of crop leaf images.
- By using deviation analysis to identify areas, the Prompt-Tuned Multi-Task Taxonomic Transformer (PTMTT) enables accurate segmentation and ensures accurate border mapping for efficient crop leaf disease detection.
- The Scale-Aware Hierarchical Auto-Associative Polynomial Network (SA-HAAPNet) successfully classifies agricultural leaf diseases following feature extraction, with enhanced prediction accuracy and discrimination among various disease types.
- The efficiency of the identification process is enhanced by the Walk-Spread Algorithm (WSA), which maximizes the search for ill areas while enhancing classification accuracy and reducing errors.

II. LITERATURE REVIEW

In 2025, Srinivasan et al. [18] have presented with deep neural networks for sugarcane leaf disease classification. DenseNet201 and EfficientNet-B7, among other ConvNet models, were trained and validated on the Sugarcane Leaf Image Dataset (SLD) with 6748 images for 11 disease classes. The highest accuracy belonged to EfficientNet-B7 at 99.79%, with DenseNet201 at 99.50% being the next. 5-fold cross-validation was used to ensure stable evaluation. Disadvantages are model complexity and computational requirements, but advantages are high accuracy, automation, and faster disease detection. The present research indicates that deep learning has the capability of enhancing crop production and enhancing sugarcane disease identification. In 2023, Aakash Kumar et al. [19] have presented, with a convolution neural network system, sugarcane leaves can be distinguished as being healthy or diseased. VGG-16 and VGG-19 CNN models were trained with the Sugarcane Leaf Image Dataset from Kaggle with 2165 images of healthy and diseased leaves. VGG-19 had 92% accuracy and 90% precision, with early identification of the disease with drone-based farm monitoring. While its disadvantages are low performance on complex patterns and high computational complexity, its advantages are early intervention and quick, precise disease recognition. The technique enhances crop health and yield and assists in a timely control of diseases. In 2023, Sun et al. [20] have presented, SE-Vision Transformer: A hybrid network employing an attention mechanism to identify issues of sugarcane leaves. The SE-ViT hybrid network for the identification of sugarcane disease was implemented using the Sugarcane Leaf Image Dataset. Due to its improved segmentation accuracy, SVM was chosen for leaf lesion extraction. The model improves accuracy by 5.1% by integrating SE attention into ResNet-18, multi-head self-attention (MHSA), and 2D relative positional encoding. It attains 89.5[illegible]% accuracy on sugarcane data and 97.26% accuracy on Plant Village. Although complexity and computational demands continue to be obstacles, advantages include increased accuracy and precision.

In 2025, Kuppusamy et al. [21] have presented Improving sugarcane leaf disease identification with a unique hybrid shifted-vision transformer method: technological insights and methodological breakthroughs. The Sugarcane Leaf Image Dataset was utilized to construct a Hybrid Shifted-Vision Transformer for automated sugarcane disease classification. Hybrid Shifted Windows and Vision Transformer (ViT) are combined in this model to capture both local and global features. Self-supervised learning with data augmentation (rotation, flipping, occlusion, and jigsaw puzzles) increases feature representation. It has a 98.5% accuracy rate and addresses class imbalance through stratified sampling. High accuracy and effective large-scale monitoring are benefits; however, complexity and computing cost are drawbacks.

Problem Statement:

Crop leaf diseases are a serious risk to agricultural output because they can result in large production losses and negative economic effects. For illness care to be effective, early and precise detection is essential. In order to facilitate timely intervention, reduce crop loss, and improve agricultural sustainability, this study intends to create a sophisticated machine-learning model for automated crop leaf disease prediction.

III. PROPOSED METHODOLOGY

The suggested Wavelet Prompt-Tuned Multi-Task Taxonomic Transformer with Hierarchical Auto-Associative Polynomial Network (WATT-Net) for crop leaf disease identification using the Sugarcane Leaf Image Dataset is shown in block diagram form in Figure 1. To improve image quality by minimizing noise and blurring, the process starts with pre-processing using Discrete Wavelet Transformation with Pre-Gaussian Filtering (DWT-PGF). Next, the Prompt-Tuned Multi-Task Taxonomic Transformer (PTMT) is used to segment, identifying regions using deviation analysis for precise border detection. Finally, the Scale-Aware Hierarchical Auto-Associative Polynomial Network (SA-HAAPNet) is used to obtain classification for efficient illness detection. Through the optimization of the search process for affected regions, precision is improved by the Walk-Spread Algorithm (WSA). The method has superb detection ability by classifying sugarcane leaves into five categories: Healthy, Red Rot, Mosaic Disease, Rust, and Yellow Leaf Disease.

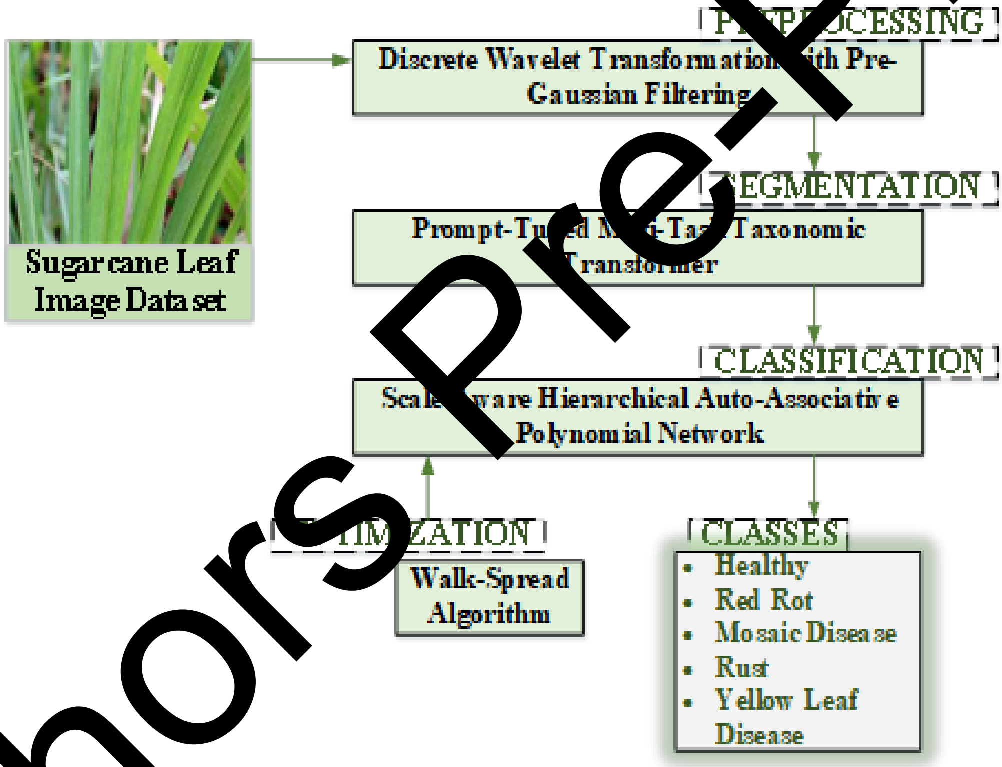


Fig 1.Block diagram of proposed WATT-Net

A. Data collection

The data set of sugarcane leaf disease image adopted in this study contains a total number of 2521 high resolution images which are properly classified into five categories of disease namely: Healthy (522), Mosaic (462), Red Rot (518), Rust (514), and Yellow Leaf Disease (505). Such equalization does not make the model biased to a specific class, which promotes fair training and evaluation. Real-world agricultural conditions prompted the gathering of the images via mobile phones and DSLR cameras, and these images feature different lighting, different backgrounds, and different orientations of leaves in diverse situations. The dataset was made to be accurate, and therefore each image was labeled manually by agricultural experts. Mosaic disease is indicated by the mottling pattern of light and dark green leaves which mostly occur as a result of viral infection; Red Rot is a severe fungal infection that is characterized by reddish discoloration and deterioration of internal parts; Rust appears in the form of brown pustules on the surface of the leaves as a result of fungal infection; and Yellow Leaf Disease is characterized by the progressive yellowing of the leaves starting with the midrib towards the periphery usually as a result of viral pathogens infection. Access to the source of the dataset could be found at the following link: https://www.kaggle.com/datasets/nirmalsankalana/sugarcane-leaf-disease-dataset?select=Yellow. The data acts as a strong benchmark towards the development and testing of deep learning algorithms used in the automatic classification of sugarcane leaves into healthy and unhealthy status to aid in early diagnosis of crops in precision farming. In a bid to improve generalization of the models, rotation, flipping, zooming among other data augmentation methods were used in the preprocessing of the data.

B. Preprocessing using Discrete Wavelet Transformation with Pre-Gaussian Filtering (DWT-PGF)

The first stage of the pipeline is Discrete Wavelet Transformation with Pre-Gaussian Filtering (DWT-PGF) that improves the quality of images by removing noise, as well as keeping important structural information. Gaussian filter is good at smoothing the image and deleting the high-frequency noise, preserving the significant details, such as the edges of the leaves and the patterns of veins. DWT is then used to break the image down into several frequency sub-bands, allowing the exact separation of meaningful features to be isolated. In further enhancement of the image, soft and hard thresholding is used to shut down irrelevant wavelet coefficients that would bring cleaner and sharper images of the disease-affected regions. This preprocessing step enhances the image clarity to a great extent and also sets the stage for accurate segmentation in the later stages. With noise reduction and improved image clarity, the Discrete Wavelet Transformation with Pre-Gaussian Filtering (DWT-PGF) [22] process improves sugarcane leaf images in the Sugarcane Leaf Image Dataset in such a way that sugarcane leaf diseases are better recognized and classified. Preprocessing of images was performed in this study using Discrete Wavelet Transform (DWT) to improve the quality and features of the sugarcane leaves images. This explains why wavelet-based filtering process should be preferred over other conventional enhancement methods; the multi-resolution analysis power. The spatio-frequency information can be localized without interpolating by DWT, thus a fine detail texture variation and subtle representation disease modeled in a leaf image can be established using DWT. Whereas other spatial filters (e.g., Gaussian or median filters) can be used either to smooth the image and reduce noise, or put emphasis on edges, DWT works to maintain useful information on texture and context within the image by decomposing it into a variety of frequency sub-bands. Such decomposition facilitated the identification of guidelines with respect to the features of the disease, and it also helped to desolate the irrelevant background noise, thus enhancing the feature extraction and classification by outturning the performance. The fact that wavelet transforms can change to suit both smooth areas as well as sharp discontinuities make them particularly appropriate in their application to complex biological textures such as in plant pathology.

1)Gaussian Filter

The importance of the Gaussian filter as a preprocessing step on the Sugarcane Leaf Image Dataset is to remove noise in the image and maintain significant spatial structures (leaf edges and vein patterns). It operates by blurring the image with a weighted average, with weights given by a two-dimensional Gaussian distribution. This is performed to suppress undesirable high-frequency changes due to lighting variations, noisy sensors, or other environmental changes, which improves the overall image clarity without much blurring of edges. Sugarcane Leaf Image Dataset needs to be pre-processed so that noise can be eliminated while preserving edges and spatial information. By reducing the undesired variations and offering smoothness, Gaussian filtering enhances the clarity of images. The Gaussian filter for two-dimensional (2D) image processing is represented by equation (1):

$$G_{\mu}(u,v) = \frac{1}{2\pi\mu^2} e^{-\frac{(u^2+v^2)}{2\mu^2}} \quad (1)$$

where, u and v display the horizontal and vertical axes together with their separation from the centre. μ represents the distribution of standard deviations.

2)Discrete Wavelet Transformation (DWT)

Discrete Wavelet Transformation (DWT) is an effective image preprocessing method that can be applied in transforming the sugarcane leaf images into wavelet domain to be able to remove noise and enhance the images to detect diseases. In DWT, the scaling factor and the translation variable are discretized and this enables the image to be analyzed in a multi-resolution analysis manner. The mathematic formulation of the transformation is a summation of wavelet basis functions operated on a square-integrable function, which is an image. This operation breaks the image down into various frequency sub-bands, usually low-low (LL), low-high (LH), high-low (HL), and high-high (HH), each with particular directional and frequency content. The translation variable and scaling factor are discretized. The DWT is expressed mathematically in equation (2).

$$DWT_g(u,v) \leq f(g), \psi_{u,v}(g) \geq \int_P f(g) \bar{\psi}_{u,v}(g) dg \qquad (2)$$

where, $f(g)$ is symbolize the square-integral function. $\psi(g)$ is illustrate how wavelet bases work. Sugarcane leaf images from the Sugarcane Leaf Image Dataset are transformed into wavelet space using wavelet transformation, which allows noise reduction and image enhancement for precise sugarcane leaf disease detection. For accurate reconstruction, wavelet coefficients below the threshold in Equations (3) and (4) are zeroed.

$$(Soft) S'_{u,v} = \begin{cases} \operatorname{sgn}(S_{u,v})(\langle S_{u,v} \rvert - F), & \lvert S_{u,v} \rvert \geq F \\ 0, & \langle S_{u,v} \rvert < E \end{cases} \qquad (3)$$

$$(Hard) S'_{u,v} = \begin{cases} S_{u,v}, & \lvert S_{n,m} \rvert \geq F \\ 0, & \langle S_{n,m} \rvert < F \end{cases} \qquad (4)$$

where, the soft thresholding is represented by equation (3). The hard thresholding is represented by equation (4). These thresholding functions are used in wavelet transformation to eliminate noise by altering wavelet coefficients based on a threshold value F .To enhance feature extraction and ensure precise disease region detection, segmentation is performed to pre-processed sugarcane leaf images.

C. Segmentation using Prompt-Tuned Muti-Task Taxonomic Transformer (PTMT)

The novelty of the Prompt-Tuned Multi- Task Taxonomic Transformer (PTMT) is that it combines prompt learning, multi-task learning, and taxonomic hierarchy modelling in a transformer framework. PTMT, in contrast to the traditional segmentation models, is trained to jointly process many tasks, including segmentation, hierarchical classification, and severity estimation, using a shared input token sequence with learnable prompt tokens. These prompts are task-specific instructions in the model that directs it to relevant features during training. In addition, PTMT incorporates hierarchical knowledge with structured [MASK] tokens, where each one of them represents a level in the taxonomy (e.g., presence of disease, type, and severity). This makes the predictions consistent with biological hierarchies, logical contradictions are minimized. The prompt tuning approach means that only the prompt tokens are optimized throughout training, keeping the model lightweight and adapts to new tasks with a minimum of fine-tuning. This makes the model more generalized and explains itself especially in real-life situations like identifying plant diseases in varying environmental conditions. To improve accuracy in the detection and segmentation of sugarcane leaf diseases, the Prompt-Tuned Multi-Task Taxonomic Transformer (PTMT) [23] segments pre-processed sugarcane leaf images from the Sugarcane Leaf Image Dataset with consideration for environmental variability. By combining Prompt Tokens and [MASK] Tokens, and eliminating manual prompt engineering while enhancing feature extraction from the Sugarcane Leaf Image Dataset, differentiable prompts trained through backpropagation enable automatic segmentation of sugarcane leaf diseases. Hierarchy levels are denoted by the $[MASK]$ token number, and the prompt token number (n) is a hyper parameter which can be adjusted. Once these tokens are incorporated, the composition of processing input token sequences is demonstrated by the equation (5).

$$[SEP],[T_1],...,[T_n],[LP_1],...,[LP_n],[MASK],...,[MASK],[SEP] \qquad (5)$$

where, $[T_1],...,[T_n]$ is represent the tokens in the given sentence. $[LP_1],...,[LP_n]$ is stand in for the learnable prompts' tokens. $[SEP]$ is symbolize the various parts of the input sequence that are separated. $[MASK]$ is shows masked tokens that correspond to the hierarchy's levels. During segmentation, the algorithm predicts sugarcane leaf disease labels by populating $[MASK]$ tokens at various hierarchical levels. Training improves the model to accurately predict diseases using the Sugarcane Leaf Image Dataset at all levels, with each $[MASK]$ token denoting a distinct label. The segmented sugarcane leaf images are then sent to the feature extraction and classification phases to guarantee accurate disease classification.

D. Feature extraction and classifications are done using Scale-Aware Hierarchical Auto-Associative Polynomial Network (SA-HAAPNet)

In order to accurately identify diseases, this part first extracts features from photos of sugarcane leaves. Next, it uses the Scale-Aware Hierarchical Auto-Associative Polynomial Network (SA-HAAPNet) to classify diseases into several groups.

1) Scale Integration with Context Awareness (SI-CA)

By combining fine- and coarse-grained information with max pooling and convolution for precise feature extraction, the Scale Integration with Context Awareness (SI-CA) [24] technique extracts multi-scale features from sugarcane leaf images, improving disease detection. This process is derived from the following equation (6).

$$SI-CA=\sum_{n=1}^{4} Conv(MaxPooling(SI-CA^{n})) \tag{6}$$

where, $SI-CA^n$ is depict the input photos with the features that were retrieved.

2) Meet Transformer (MT)

Meet Transformer (MT) is an effective architecture used in sugarcane leaf disease analysis, which is borrowed to improve feature extraction using a multi-head self-attention mechanism. In contrast to the conventional convolutional methods, MT models long-range spatial dependencies over the whole image, modelling the relations between all regions of the pixel space at once. This feature is useful especially in segmentation tasks related to diseases, as the symptoms can be located in small or disparate regions of the leaf. Input features are mapped to spatially enriched representations by the model, which preserves local textures and global context. These improved features are subsequently input to the classification block which identifies the kind of disease on them. The MT model enables segmenting the sugarcane leaves accurately and classifying the diseases with high precision, as it takes advantage of the power of attention mechanisms. Using multi-head self-attention to capture spatial dependencies and improve disease segmentation accuracy, the Meet Transformer (MT) model extracts feature from sugarcane leaf images. The feature extraction process is defined by the formula in equation (7).

$$MT(SI-CA)=softmax(Transformer\ Encoder(SI-CA^{n})) \tag{7}$$

where, $SI-CA^n$ is symbolize the spatially enhanced features for further processing. The classification block gets the features discovered from these photos in order to determine the classifications of crop leaf diseases.

3) Hierarchical Auto-Associative Polynomial Network (HAAPNet)

By incorporating a polynomial layer into CNNs, the Hierarchical Auto-Associative Polynomial Convolutional Neural Network (HAAP-CNN) [25] enhances non-linear feature learning and raises classification accuracy across several disease categories, improving sugarcane leaf disease classification. Using equation (8), a polynomial layer is placed following the input image or pooling layer to improve the classification accuracy of sugarcane leaf disease.

$$h_{\omega 1}(a,b,c,n)=h_{\omega 0}(a,b,c)^{n} \tag{8}$$

where, $n=1,2,...,N.$ This is accomplished by combining the across-dimension with a traditional CNN, which allows the forward motion to proceed normally for the remaining portions of each iteration. $\omega=1,2,...,P.$ As a result, the weight parameters are adjusted accordingly and all completely linked layers are treated similarly. Below is the final classification equation (9).

$$d\tau 1(j,n)=d\tau 0(j)^{n} \tag{9}$$

where, $\tau=1,2,...,\tau.$ This procedure is performed for every iteration until the recognized categories are accurately defined in order to guarantee appropriate classification of sugarcane leaf diseases. Whereas the standard CNNs chiefly depend on linear combinations of local features, and the Vision Transformers (ViTs) are concerned with global attention mechanism on the need of huge dataset, HAAPNet presents hierarchical polynomial expansions that allow me to model complex as well as non-linear dependencies more competently even by using a moderate-sized dataset. Auto-associative mechanism makes textural encoding on memory-based feature textures and the polynomial layers introduce the discriminative capability by detecting fine-grained and multi-scale disease attributes, such as speckling, edge deformation, and discoloration. This provides HAAPNet with an advantage compared with CNNs in modeling disease regions with high variability and compared with ViTs in learning relatively efficiently due to limited data and computation.

Loss Function: Equation (10), which represents the loss function for the Scale-Aware Hierarchical Auto-Associative Polynomial Network (SA-HAAPNet), ensures robust classification performance.

$$Loss = \frac{1}{N}\sum_{j=1}^{K}(y_j - \hat{y}_j) + \rho\|V\|^2 \tag{10}$$

where, $Loss$ is symbolize the whole loss. y_j and $\hat{y}_j$ are a representation of the actual and expected outcomes. V is symbolize the network's weights. ρ is make adjustments to the regularization value to prevent overfitting. The Walk-Spread Algorithm (WSA) is used to optimize the classification loss function.

E. Walk-Spread Algorithm (WSA)

The Walk-Spread Algorithm (WSA) is an advanced population-based metaheuristic optimization approach that draws inspiration from natural movement and information dissemination patterns. It operates by simulating the "walking" of agents through a high-dimensional search space, combined with a "spreading" mechanism that allows information about the best-performing solutions to guide the population toward optimal regions. This dual behavior helps maintain a balance between exploration (diversifying the search to avoid local optima) and exploitation (intensifying the search around promising solutions). WSA is designed to efficiently optimize complex, non-convex, and multi-modal objective functions by iteratively updating candidate solutions based on adaptive movement rules and local-global feedback. Its theoretical foundation lies in enhancing convergence behavior and search diversity, making it particularly effective in fine-tuning parameters for deep learning and classification tasks. By minimizing the loss function, the Walk-Spread Algorithm (WSA) [26], an advanced optimization technique, enhances the classification of sugarcane leaf diseases and enables the model to recognize subtle disease patterns for precise diagnosis. For sugarcane leaf disease detection application, WSA is important in improving the specificity of the region identified as affected with disease by repeatedly sharpening up the segmentation and classification frontiers. Instead of using only the static, gradient-based optimizers, WSA progressively changes the partitioning border in space and the feature border inside the segmented regions due to the fitness-guiding feedback. This gives a more accurate assessment in relation to the reality of the leaf pathology in the disease-affected areas, particularly where symptoms are diffuse, irregular and can be seen visually as being ambiguous.

Step1: Initialization

The Walk-Spread Algorithm (WSA) selects the best-performing search agents for optimization following the initialization of an estimated population of search agents and parameter definition. The WSA then uses the SA-HAAPNet loss function to evaluate fitness.

Step2: Random Generation

Random Generation improves the Walk-Spread Algorithm (WSA) by adding varied search agents, avoiding premature convergence, and encouraging exploration. Random Generation starts with the generation of random agents, ensuring diversity, checking fitness, and choosing best solutions.

Step3: Fitness Function

The fitness function, as defined in the context of the Scale-Aware Hierarchical Auto-Associative Polynomial Network (SA-HAAPNet) optimization process is intended to drive the optimization process by measuring the quality of the candidate solutions with respect to two main objectives: classification accuracy and energy efficiency. The SA-HAAPNet fitness incorporates scale-awareness, i.e. it takes into consideration the changes in spatial scale and feature significance across hierarchical levels, and along with this, it incorporates polynomial relationships among features to create a deep, non-linear encoding of the data. The auto-associative part makes sure that the network is capable of learning minimal, self-reconstructing representations, useful to keep only the most informative features.

This fitness balances the tradeoff between obtaining high predictive performance (minimizing the misclassifications errors) and computational efficiency (minimizing power or resource usage during model execution). It is a key to stable convergence, where it avoids overfitting or underfitting by adjusting the structure or parameters of the model during training. An effective fitness function is well-designed such that the optimization algorithm has a way of distinguishing between a poor (suboptimal) and a good solution (optimal), and this helps direct the search towards the right direction in the high-dimensional space (or complex space) that characterizes many image-based classification problems, such as the diagnosis of sugarcane leaf diseases. Equation (11) illustrates the mathematical formulation of the Scale-Aware Hierarchical Auto-Associative Polynomial Network (SA-HAAPNet) fitness function, which balances classification accuracy and energy savings to assess optimization quality, guarantee stable convergence, and minimize misclassification errors. More importantly, this task allows testing the model at discerning affected health regions, and then Template-based segmentation mapping boundaries can be changed, and regional accuracy can be improved. This walking-based refinement can help make the model sensitive to high-resolution regional clues, e.g. edge distortion or regional discoloration and refine detection and boundary segmentation.

$$Fitness = Min[\frac{1}{N}\sum_{j=1}^{K}(y_j - \hat{y}_j) + \rho\|V\|^2] \tag{11}$$

where, $\frac{1}{N}\sum_{j=1}^{K}(y_j - \hat{y}_j) + \rho\|V\|^2$ is represent the loss function of SA-HAAPNet.

Step4: Improve the quality of the corresponding unit

The Walk-Spread Algorithm (WSA), which improves feature mapping accuracy through quality-based directional modifications, employs two walks for sugarcane leaf disease detection: one towards the best disease representation of features and another towards a target set of features with shuffled feature mappings. Updating the pertinent unit is expressed in equation (12).

$$v'_{n,m} = \begin{cases} H_{best}, & g(H_{best}) < g(v_{n,m}) \\ v_{n,m}, & \text{otherwise} \end{cases} \tag{12}$$

where, $g(H_{best})$ is the objective function that evaluates the quality of the answer. If the candidate solution's function value, H_{best} is greater than that of $v_{n,m}$, then the update takes place; if not, $v_{n,m}$ remains intact.

Step 5: Termination

Until the maximum iteration limit or predetermined accuracy and fitness thresholds are reached, the sugarcane leaf disease detection algorithm continues to run iteratively. If there is no discernible progress, the algorithm stops, guaranteeing the best possible disease classification results.

IV. RESULTS AND ANALYSIS

The suggested approach is compared to current analytic methods after being implemented and assessed on the Python platform. Table 1 provides a detailed description of the simulation's parameters as well as an analysis of the results.

TABLE I: Simulation Specifications

Specifications	**Description**
Programming Language	Python
Version	3.7.14
OS	Windows 10
Dataset	**Sugarcane Leaf Image**

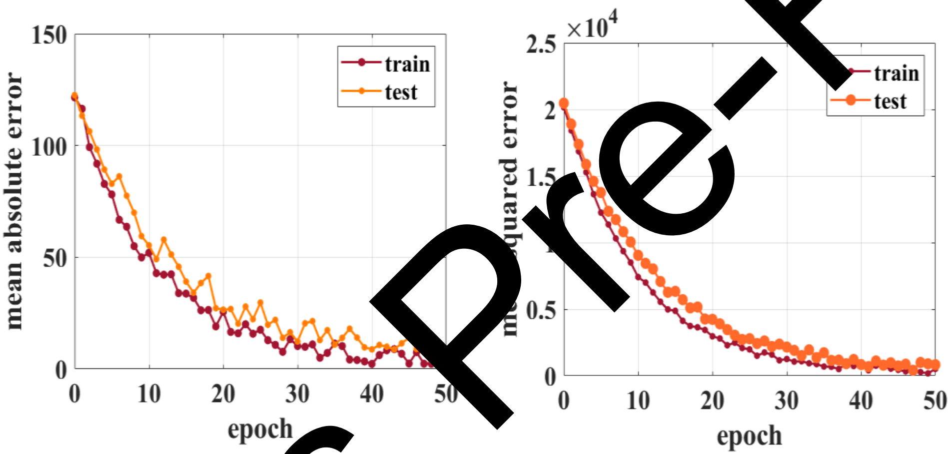
Diseases	○ Healthy ○ Red Rot ○ Mosaic Disease ○ Rust ○ Yellow Leaf Disease
Training network	Scale-Aware Hierarchical Auto-Associative Polynomial Network (SA-HAAPNet)
Algorithm	Walk-Spread Algorithm (WSA)

A. Description of the Dataset

❖ **Sugarcane Leaf Image dataset**

In order to properly identify and categorize different sugarcane leaf illnesses, deep learning models are trained and evaluated using images of both healthy and diseased sugarcane leaves from the Sugarcane Leaf Image Dataset.

4.2 Performance Analysis of Sugarcane Leaf Image dataset



(a) (b)

Figure 2: (a) mean absolute error (b) mean squared error of Sugarcane Leaf Image Dataset

The model's performance on the Sugarcane Leaf Image Dataset is shown in Figure 2. (a) Demonstrates enhanced prediction accuracy by showing the mean absolute error (MAE) gradually declining over 50 epochs for both training and testing sets. (b) Shows the decrease in mean squared error (MSE), which indicates improved model generalization. The model's convergence and efficacy in detecting leaf diseases are indicated by both metrics.

TABLE II: Performance Analysis of WATT-Net

Metrics	**Diseases**	**(ENetB7-DNet201) [18]**	**(VGG16-VGG19) [19]**	**(SE-ViT-SVM) [20]**	**(HSW-ViT) [21]**	**Proposed Technique (WATT-Net)**
Accuracy%	Healthy	83.4	83.9	85.3	86.4	99.8
	Red Rot	88.8	89.2	84.5	86.4	99.9
Precision%	Healthy	81.5	86.1	87.3	84.9	98.8
	Red Rot	87.7	92.9	86.2	89.8	97.9
Recall%	Healthy	83.1	88.7	85.4	87.4	99.9
	Red Rot	86.8	83.4	81.8	84.1	99.9
Sensitivity%	Healthy	87.4	85.5	83.1	88.3	99.8
	Red Rot	86.6	87.2	88.9	83.8	99.7
Specificity%	Hea lthy	87.2	83.4	85.9	89.9	98.8

	Red Rot	89.9	87.4	84.8	81.7	98.8
F1-score%	Healthy	81.3	89.4	83.1	87.5	99.9
	Red Rot	83.1	88.9	85.2	89.6	97.8

The performance analysis of the WATT-Net strategy for crop leaf disease identification is shown in Table 2 in comparison to the current approaches (ENetB7-DNet201, VGG16-VGG19, SE-ViT-SVM, and HSW-ViT). With the best accuracy (99.9%), precision (98.8%), recall (99.9%), sensitivity (99.8%), specificity (98.8%), and F1-score (99.9%) for both the Healthy and Red Rot categories, WATT-Net performs better than any other method.

V. CONCLUSION

The difficulties in identifying agricultural leaf diseases are successfully addressed by the Wavelet Prompt-Tuned Multi-Task Taxonomic Transformer with Hierarchical Auto-Associative Polynomial Network (WATT-Net). This approach increases the precision and reliability of disease detection through solving the problems like the requirement of enormous datasets, environmental instability, and complexity of prediction in real time. Reducing blurring and noise, the pre-processing stage of Discrete Wavelet Transformation with Pre-Gaussian Filtering (DWT-PGF) increases the image quality. The Prompt-Tuned Multi-Task Taxonomic Transformer (PTMT) uses deviation analysis for detecting regions so that segmentation can be carried out accurately. Even though the Walk-Spread Algorithm (WSA) optimizes the search process for damaged areas, classifying with higher accuracy and less error, the Scale-Aware Hierarchical Auto-Associative Polynomial Network (SA-HAAPNet) effectively identifies diseases following feature extraction. With 99.9% efficiency and 99.8% sensitivity, the Sugarcane Leaf Image Dataset experimental results show better performance and give a trustworthy method for agricultural analysis.

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