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Synergizing Image Processing and Deep Learning for Precise Pollen Classification

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Abstract: Pollen classification is a critical task with applications spanning diverse fields such as botany, geology, ecology, and evolutionary biology. Existing identification methods suffer from labor-intensive processes, time constraints, and dependency on highly skilled experts. This research addresses the exigent need for an automated and precise pollen identification system through the introduction of a novel hybrid approach. The proposed hybrid model combines advanced image processing techniques with deep learning methodologies to achieve accurate and efficient pollen recognition. Initial noise reduction is accomplished through the application of a Wiener filter, followed by the utilization of pixel properties for image reflection removal. Subsequently, the Scale Invariant Features Transform (SIFT) is employed for robust feature extraction. The final stage involves the application of a Convolutional Neural Network (CNN) for pollen classification. Experimental results demonstrate the superiority of the hybrid model, exhibiting significantly higher accuracy and classification performance. The precision value of 0.9937, recall of 0.9918, F1-Score of 0.9999, and an overall accuracy of 99.91% underscore the efficacy of the proposed approach. This innovative integration of image processing and deep learning not only addresses the shortcomings of existing methods but also sets a new standard for precise and automated pollen classification, offering invaluable contributions to various scientific disciplines. This research holds promising potential to revolutionize the field by providing a scalable and efficient solution to the longstanding challenges associated with pollen identification.

Keywords: Pollen Classification, Wiener Filter, Pixel Properties, SIFT, CNN

1. Introduction

Identifying and classifying pollen is crucial across various fields like ecology, agriculture, paleoecology, paleoclimatology, environment, archaeology, medicine, botany, and forensics [1], [2]. However, traditional methods for pollen analysis pose significant challenges due to their labor-intensive nature and the high level of expertise needed for accurate classification. These conventional techniques, heavily reliant on microscopy, involve meticulous processes and are prone to human error, highlighting the necessity for more efficient and reliable methods [3], [4].

Automating identification using Deep Learning (DL) algorithms provides several benefits. These include reducing the time and effort required for analysis, increasing the accuracy and consistency of results, and enabling large-scale analysis of pollen samples. This process can bring new insights and discoveries in many fields [5], [6].

In recent years, deep learning has been widely used to increase efficiency and accuracy, reduce human effort and reduce errors [7]. Among various deep learning (DL) techniques, convolutional neural networks (CNN) have become popular in the last few years. They are known for their performance in tasks such as image classification, object detection, and task recognition. This is attributed to powerful neural network architectures that can autonomously extract mid- to high-level features from image

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datasets and make them more interesting [8[–[10].

However, CNNs inherently possess limitations, particularly in capturing fine-grained textural details crucial for distinguishing visually similar pollen. Pollen displays intricate surface textures and patterns that vary significantly between species, making texture analysis essential for accurate classification. Moreover, CNNs often demand substantial amounts of labeled data for effective training, a challenge due to the labor-intensive nature of data annotation in pollen classification [11], [12]. To overcome these limitations, this study employs a hybrid method that integrates image processing techniques with Convolutional Neural Network (CNN) technology. The application of the Wiener filter is pivotal in mitigating noise, providing a cleaner foundation for subsequent analyses. Utilizing pixel properties for image enhancement further refines the visual characteristics of pollen samples, contributing to more accurate feature extraction. SIFT plays a crucial role in capturing distinctive features of pollen, particularly their complex surface textures.

While CNNs excel in recognizing overall patterns, they may struggle with fine-grained details essential for distinguishing visually similar pollen. The hybrid model leverages the strengths of each component, combining the precision of traditional image processing techniques with the ability of CNNs to recognize complex patterns. This synergy enhances the overall accuracy and efficiency of pollen classification in diverse and challenging scenarios. Notably, this integration also reduces the amount of data required for CNN training, enabling more efficient model training and classification [13], [14]. This combined approach capitalizes on the strengths of both techniques, improving feature extraction and yielding more robust and accurate results in pollen classification.

The paper is organized as follows: the first chapter presents the introduction, followed by a detailed discussion of existing literature in Chapter Two. Methodology is comprehensively described in Chapter Three, and the results and discussions are expounded upon in Chapter Four.

2. Literature Review

Traditionally, pollen analysis has relied on manual microscopy, a labor-intensive process demanding skilled experts [15]–[17]. This technique involves both bright field and dark field microscopy, and can incorporate various pollen preparation approaches like staining fresh pollen or acetolysis [18], the latter being applicable to fossil pollen as well [12]. While manual microscopy remains the favored choice for certain applications, ongoing technological advancements are introducing alternative methods. These include molecular techniques like meta-barcoding [19] or genome skimming [20], chemotaxonomy [21], and image analysis methods utilizing deep neural networks [21], [22].

For pollen analysis methods to be valuable, they must possess qualities of accuracy, quantifiability, efficiency [23], [24], and ideally, be accessible to a broad user base. The accuracy, primarily gauged by correct identification, is generally presumed to be high in manual analysis [23]. Nevertheless, some studies indicate lower accuracy levels in human assessments [25], and despite their quantitative nature [26], manual methods are relatively inefficient. A common challenge is the trade-off between the number of samples and the quantity of analyzed pollen grains per sample, leading to increased uncertainty in quantitative estimates [16], [26]. While there is a claim that meta-barcoding can facilitate quantitative assessments [19], this perspective has faced opposition [27].

Image analysis methods employing neural network or machine learning classification techniques hold the potential to achieve accuracy, quantifiability, efficiency, and accessibility. A recent review by Holt and Bennett [23] highlights the potential and requirements of using hybrid methods. Many new studies have since been published [12, 28, 29], indicating substantial advancements in the field of image processing and deep neural network. Notably, deep neural networks, particularly convolutional neural networks (CNN), have demonstrated high efficiency in classifying two-dimensional images [30]–[33].

Recent studies have demonstrated remarkable accuracies, approaching nearly 100% [12], [29], [34]. Even when faced with a challenging task involving 46 pollen types. Sevillano et al. [28] demonstrated an impressive correct classification rate of nearly 98%. This achievement is particularly noteworthy considering that some of the included pollen types are traditionally difficult to distinguish, even for experienced palynologists.

The results from a convolutional neural network (CNN) classification are not only accurate but also quantitative. With contemporary computing capabilities, the classification process is highly efficient, with the ability to classify a hundred or more objects per second [29]. Additionally, most of the software used in these studies is built on open-source code, allowing for the potential development of open systems. Significantly, successful studies were employed hybrid methods, combining CNN with feature extraction [28], [29].

This study, we employed a hybrid method to achieve precise pollen classification. The comprehensive methodology underpinning the study is expounded upon in the subsequent chapters. These chapters provide an in-depth exploration of the intricacies involved in our approach, offering a detailed roadmap for understanding the hybrid method's application and significance in the context of accurate pollen classification.

3. Materials and Methods

The methodology comprises four distinct stages. Firstly, noise reduction is applied to pollen images, followed by reflection removal. The subsequent stage involves feature extraction, and the final step entails pollen classification utilizing Convolutional Neural Networks (CNN). The holistic flow of the methodology is visually depicted in Figure 1, providing a clear and concise overview of the sequential processes involved in our approach.

3.1. Dataset

This study utilized datasets, namely the Malaysian Pollen Dataset (MPD) to assess the efficiency and accuracy of the proposed model in classifying pollen grains across diverse geographical and botanical contexts. The MPD was collected from various locations in Terengganu, a state in Malaysia. The analysis involved 40 classes of MPD, each comprising more than 350 images, including augmented images. Figure 2 visually represents the Malaysian Pollen Datasets, offering a comprehensive overview of the dataset used in this study. In Figure 3, we present the distribution of images within the Malaysian Pollen Dataset, providing insights into the composition and variety encapsulated in our dataset.

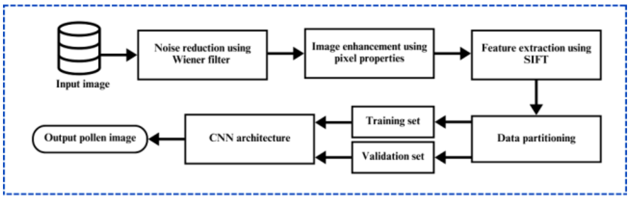


Figure 1. Overall research methodology.

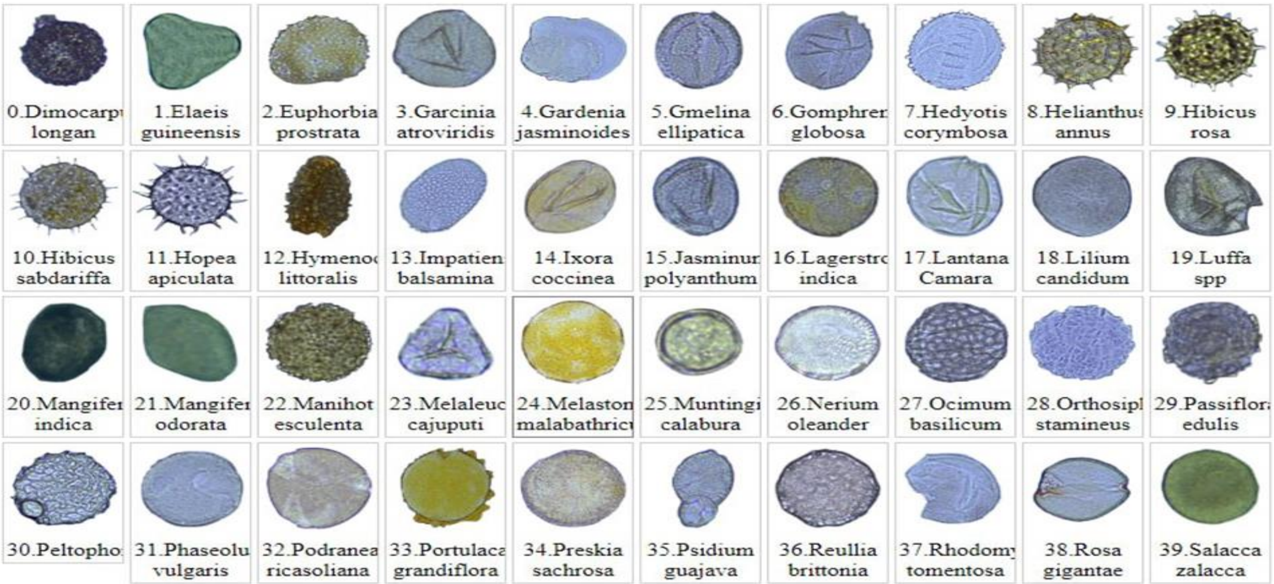


Figure 2. Malaysian pollen datasets

3.2. Noise removal using Wiener Filter

Pre-processing encompasses a set of techniques and operations applied to an input image before undertaking the actual analysis or manipulation of the image's content [35], [36]. The primary goal of pre-processing is to enhance the image's quality, render it more suitable for a specific task, or eliminate unwanted artifacts or noise, playing a crucial role in object classification. Hence, pre-processing proves essential for elevating the quality of pollen images within the collected dataset. Figure 4 illustrates the methodology flow employed for noise reduction.

In this study, the Wiener filter was utilized to reduce noisy pollen images, especially deblur. The Wiener filter, functioning as a deconvolution technique, reduces image blurriness by estimating and reversing the effects of blur in the frequency domain [37], [38]. This method proves effective when a reliable estimate of the point spread function (PSF) and noise characteristics are available. Nevertheless, its applicability may be limited in real-world scenarios featuring complex or unknown blur and noise patterns. Consequently, this research will adapt the existing algorithm to determine appropriate parameters for unknown blur, estimated PSF, and noise patterns. Striking the right balance between reducing blur and avoiding noise amplification in the process remains crucial. Figure 5 provides an example of a pre-processed image using the Wiener filter.

Firstly, we estimate how light from a point source spreads across the image to arrive at the Point Spread Function (PSF). A comparison between the noisy pollen image and this predicted PSF is made possible.

The estimated point spread function (PSF) and the noisy image are transformed from the time domain to the frequency domain using the Fast Fourier Transform (FFT). When the noise power is measured across many frequencies, the Power Spectral Density (PSD) can be calculated. Estimates are made on the noise's characteristics, such as its statistical distribution and its additive noise.

The noisy pollen image is deblurred using the widely-respected Wiener filter. This filter works by decreasing the volume of low-frequency sounds while increasing the volume of high-frequency sounds. In the frequency domain, the Wiener filter is realized by performing point-wise multiplication. The formula for the Wiener filter, denoted as H(w) is defined in Equation (1).

$$H(w)=\frac{G(w)}{G(w)+H(w)} \tag{1}$$

where *G(w)* is the FT of pollen image, and *N(w)* is the calculated NPS.

Finally, the inverse Fourier Transform is applied to the product of the filter employment in the spatial domain. This comprehensive approach significantly enhances the quality of the noisy pollen image in the dataset, effectively reducing the blur effect and bringing out the distinct features within the images.

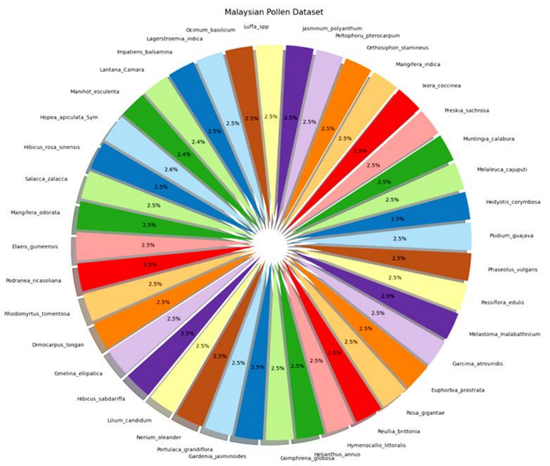


Figure 3. Distribution of Malaysian Pollen Dataset Images

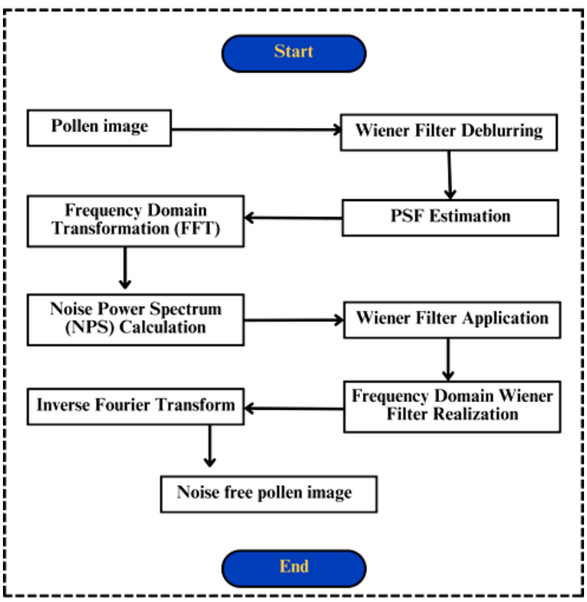
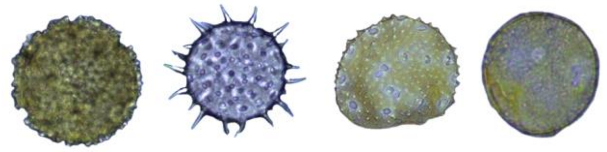
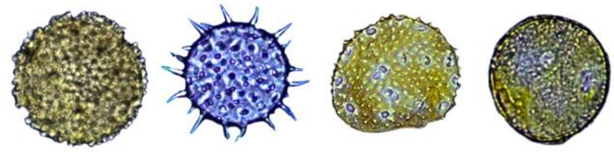


Figure 4. Flowchart for noise reduction using wiener filter.



(a)



(b)

Figure 5. Noise reduction using Wiener filter (a) Original image (b) Image after processing

3.3. Reflection removal

The method utilizes average thresholding (Equation 2) to provide a binary mask that effectively differentiates desirable pollen from background noise. By utilizing the attributes of pixels, essential characteristics such as the size and placement of components are quantified. This allows for the strategic identification of the most significant connected component, reducing potential noise's impact.

$$Threshold=\frac{1}{n}\sum_{i=1}^{n}A_i \tag{2}$$

Where n is the number of pollen images, and A_i is the grayscale value of the respective pollen region.

The process of morphological close is employed to enhance pollen morphology, while a flood-fill operation is utilized to diminish reflections, resulting in the meticulous removal of undesired deformities. Figure illustrated the overall methodologies for reflection removal employed for this study. Figure 6 illustrates the methodology flow applied for reflection removal.

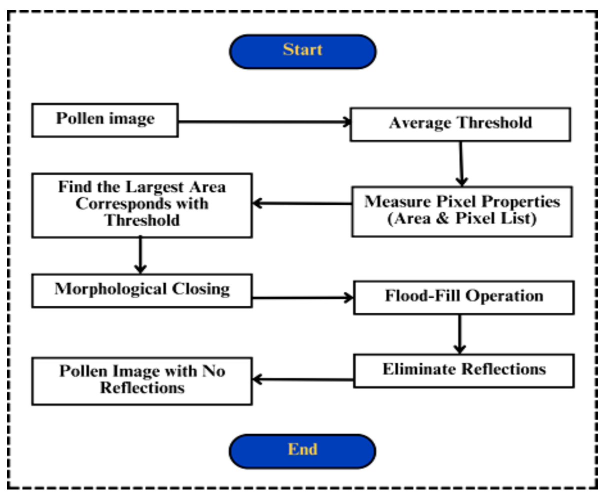


Figure 6. Flowchart for reflection removal using pixel properties.

3.4. Feature Extraction

Lowe [39] introduced a technique for extracting features called SIFT (Scale Invariant Features Transform). We have utilized SIFT for feature extraction. SIFT features are computed through a four-step process. Initially, key points that are crucial and stable for given images are identified in the local context. Following this, features are extracted from each critical point, elucidating the pollen image region samples in connection to its scale space coordinate image. In the second step, weak features are filtered out using a specific threshold value. The third step involves assigning orientations to each key point based on local image gradient directions. Ultimately, the feature vector is extracted, and bi-linear interpolation is applied to enhance the robustness of features.

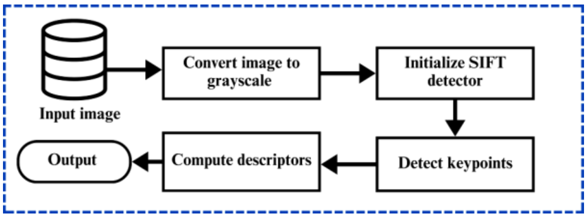


Figure 7. Flowchart for feature extraction using SIFT.

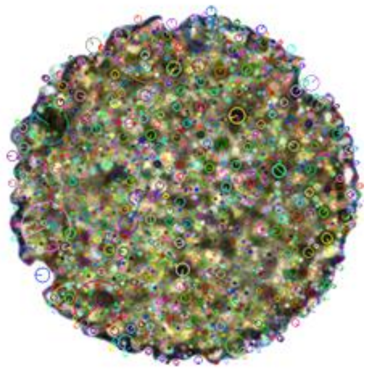


Figure 8. Example of feature selection using SIFT.

In Figure 8, the colorful circles depict key points detected by the SIFT algorithm, with the size of each circle corresponding to the scale of the detected feature. These key points are the distinctive features the algorithm has identified as invariant to scaling and rotation and partially invariant to changes in illumination and 3D camera viewpoint. These features will be used for classification using CNN.

3.5. Pollen classification

Convolutional Neural Networks (ConvNets or CNNs) were initially introduced in the 1990s, as demonstrated by LeCun et al. in 1998 [40]. However, they gained widespread popularity and recognition following the pivotal victory of AlexNet in the 2012 ImageNet competition, as reported by Krizhevsky et al. [41]. Since then, numerous modifications and variations of ConvNets have been developed, although the majority of these modifications have not been extensively applied to the classification of scattered images of airborne particles of biological origin.

In the proposed CNN Architecture, the extracted SIFT features serve as the input for the CNN model, which comprises multiple layers designed for the hierarchical extraction of high-level features from the input images. The network is trained using a portion of the labeled dataset, and performance is validated through cross-validation techniques. It is built to handle grayscale images with a default size of 48x48 pixels. Starting with the input layer, the architecture comprises a convolutional layer with six filters, each of size 5×5, and employs the 'same' padding, promising the output spatial dimensions to stay identical after convolution. Following this, a MaxPooling layer with a 2×2 pool size is employed, effectively reducing the spatial dimensions by half.

The remaining layers continue the same pattern. The model incorporates another convolution layer with 16 filters of size 5×5, including a MaxPooling operation. Following this is a third convolutional layer equipped with 64 filters of size 3×3, accompanied by an additional MaxPooling layer. After the convolutional procedures, the architecture flattens the 3D tensor to a 1D vector, which then goes via a fully connected layer containing 128 neurons and a Rectified Linear Unit (ReLU) activation function. To avoid overfitting, the model introduces a Dropout layer, which randomly sets 50% of its input data units to 0 during training. The last layer is a dense layer with 32 neurons and a softmax activation, demonstrating the model's objective to categorize input images into one of 32 and 40 possible classes for both datasets. The model working procedure is portrayed in Algorithm 1, shown in Table 1. Figure 9 represents the architecture employed on the pollen dataset.

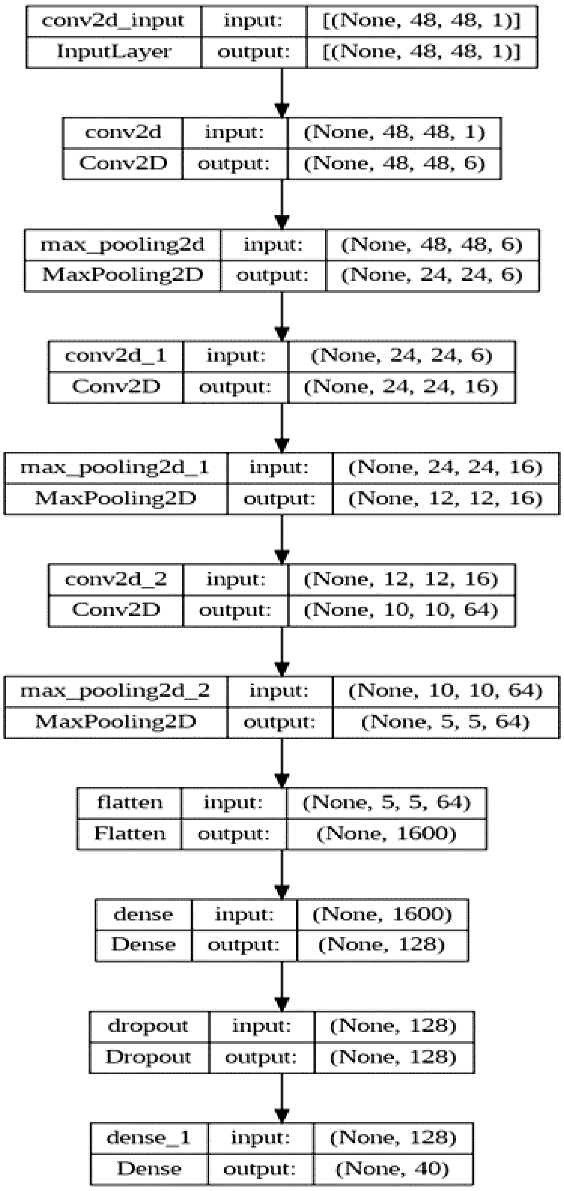


Figure 9. CNN architecture

Table 1. CNN algorithm used for this study

Algorithm 1: Pollen Image Classification Using CNN
1: **Procedure** CreatePollenModel (input_shape)
2: **if** *input_shape* is None, **then**
3: *input_shape* ← (48, 48, 1)
4: **end if**
5: **Initialize** the model as Sequential ()
6: **Add** Input layer of shape = *input_shape* ← *Convolutional Blocks*
7: **for** filters, kernel_size in [(6, (5,5)), (16, (5,5)), (64, (3,3))] do
8: model.add (Conv2D (filters, kernel_size, activation = 'ReLU'))
9: model.add (MaxPool2D(2, 2))
10: **end for**
11: **Flatten** the output
12: model.add(Dense(128, activation='ReLU'))
13: model.add(Dropout(0.5))
14: model.add(Dense(40, activation='softmax')) ← *Dataset 1*
15: **return model**
16: **end procedure**

4. Result and Discussion

Performance evaluation of the proposed method is evaluated by precision in Equation (3), recall in Equation (4), and F1-score in Equation (5). TP denotes true positives, TN signifies true negatives, FP represents false positives, and FN stands for false negatives. High precision and recall values indicate strong performance in mitigating false positives and false negatives within a model [28].

$$Precision = \frac{\sum(TP)}{\sum(TP)+\sum(FP)} \tag{3}$$

$$Recall = \frac{\sum(TP)}{\sum(TP)+\sum(FN)} \tag{4}$$

$$F1-score = \frac{2*recall*precision}{recall+precision} \tag{5}$$

The F1 score offers a comprehensive assessment by combining precision and recall. A high F1 score indicates that the model retrieved both low false positives and false negatives, demonstrating the consistency of these measures and the model's reliability. Precision, recall, and F1 scores were computed as the weighted average based on the number of actual instances for each class in our experiments. Additionally, we calculated the accuracy of the classification model by dividing the number of accurate predictions by the total number of samples. The effectiveness of the proposed CNN compared with other machine learning methods, including RF, SVM, AlexNet, MLP, and ViT.

Different pollen image classification methods are evaluated by their performance indicators, summarized in Table 2. Random Forest (RF) demonstrates robust performance with a precision of 0.9415 and recall of 0.9735, demonstrating accurate identification of positive cases and coverage of genuine positives. While the Support Vector Machine (SVM) has a somewhat lower precision of 0.8831, its recall of 0.9364 and F1-Score of 0.9926 are also remarkable, demonstrating its ability to record positive events in their entirety. AlexNet's precision is 0.99.21, but its recall is only 0.9452. The Vision Transformer (ViT) shows a balanced performance, with a high F1-Score of 0.9912 thanks to its precision of 0.9413 and recall of 0.9792. The Multi-Layer Perceptron (MLP) achieves respectable results, with a 0.9722 precision, a 0.9842 recall, and a 0.9725 F1-Score.

The Proposed Model emerges as the most promising alternative, with superior precision (0.9937), recall (0.9918), and F1-Score (0.9999) compared to all other models. This model's comprehensive and high-performing approach to pollen image classification is demonstrated by its greater capacity to produce accurate optimistic predictions while thoroughly capturing the actual positive instances. The extraordinary F1-Score of the proposed model demonstrates its remarkable equilibrium between precision and recall, making it an appealing option for this specific task. Furthermore, the accuracy of different models is shown in Figure 10.

Table 2. Comparative analysis of different methods with the proposed algorithm

Algorithms	Precision	Recall	F1-Score
RF	0.9415	0.9735	0.9811
SVM	0.8831	0.9364	0.9926
AlexNet	0.9921	0.9452	0.9452
ViT	0.9413	0.9792	0.9912
MLP	0.9722	0.9842	0.9725
Proposed model	**0.9937**	**0.9918**	**0.9999**

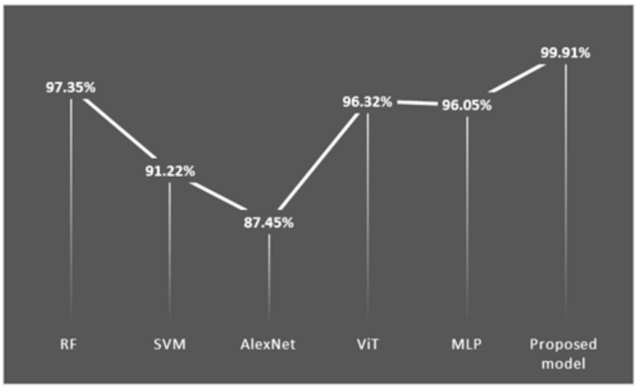


Figure 10. Accuracy comparison of the proposed model with other methods.

Confusion matrix for Dataset MPD (Figure 11) illustrating the accuracy of classifications across different categories. Heatmap of classification results for Dataset MPD. Darker squares denote higher frequencies of correct predictions. Dataset MPD's confusion matrix, the diagonal line shows the number of correct predictions, while off-diagonal elements indicate misclassifications. Number

0-39 is the index of pollen classes; refer to Figure 2 to see a sample image of each pollen class. The vertical axis represents truth values, and the horizontal axis represents predicted value. Figure 12 shows the results of pollen classification using the proposed method.

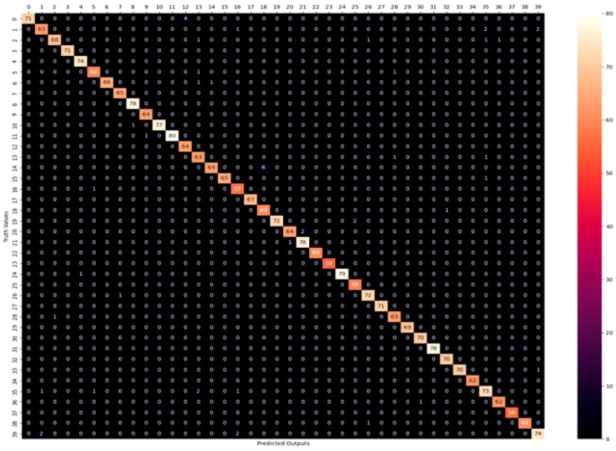


Figure 11: Confusion Matrix with Malaysian Pollen Dataset

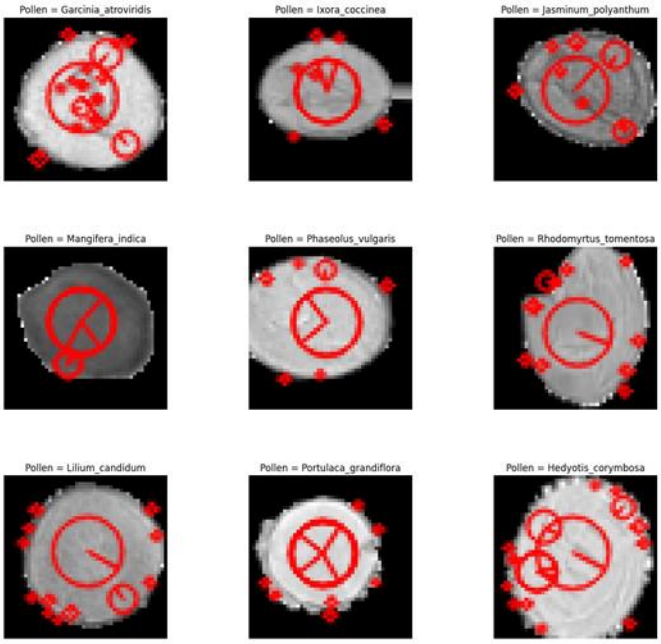


Figure 12: Confusion Matrix with Malaysian Pollen Dataset

5. Conclusion

In conclusion, this research endeavors to address the pressing need for an automated and precise pollen classification system crucial in various scientific disciplines. Leveraging a novel hybrid approach that integrates image processing and deep learning, our proposed model demonstrates significant accuracy and classification performance advancements.

The meticulous application of a Wiener filter for noise reduction, pixel properties for reflection removal, and the Scale Invariant Features Transform (SIFT) for robust feature extraction lays the foundation for the subsequent success of the Convolutional Neural Network (CNN) in pollen classification. The achieved precision value of 0.9937, recall of 0.9918, F1-Score of 0.9999, and overall accuracy of 99.91% underscore the superiority of our hybrid model compared to traditional methods.

Future research directions should focus on enhancing the proposed hybrid model by incorporating advanced techniques and expanding the dataset to encompass a broader range of pollen types. Additionally, exploring real-world applications, transfer learning, and interdisciplinary collaboration can contribute to refining the model for practical deployment in various fields.

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