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GF-CNN: A Hybrid Approach for Pollen Recognition Combining Gabor Filters and Convolutional Neural Networks

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ABSTRACT

Pollen identification is a critical task across various scientific disciplines, including geology, ecology, evolutionary biology and botany. However, existing methods for pollen identification are often labour-intensive, time-consuming and dependent on highly skilled experts, highlighting the need for an automated and precise system. This study introduces an innovative approach that combines Gabor Filters (GF) with Convolutional Neural Networks (CNN) to enhance the accuracy of pollen classification. The Gabor filters are applied to high-resolution images of diverse pollen species, accentuating texture-specific details essential for differentiation. These pre-processed images are subsequently analysed using a CNN architecture with multiple layers designed to discern hierarchical features critical for precise classification. The proposed GF-CNN model demonstrates exceptional proficiency, achieving remarkable accuracy rates of 99.85% for the Malaysian Pollen Dataset (MPD) and 99.43% for the New Zealand Pollen Dataset (NPD). These results underscore the model's ability to balance precision and recall effectively. Additionally, the model exhibits high sensitivity, indicating an increased true-positive rate, which is essential for detailed ecological studies. Furthermore, the model's improved specificity scores highlight its success in minimizing false positives, emphasizing its relevance for precision-focused research.

1. Introduction

Pollen identification and classification are indispensable techniques with applications spanning a wide range of fields, including ecology, agriculture, environment, paleoclimatology, paleoecology, archaeology, medicine, botany and forensics [1,2]. However, existing pollen analysis methods present considerable challenges due to their labour-intensive nature and the high level of expertise required for accurate classification. These techniques largely dependent on microscopy, involve meticulous processes and are often subject to human error, emphasizing the need for more efficient and reliable methods [3,4].

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The automation of the identification process through deep learning (DL) algorithms offers numerous advantages. These include the reduction of time and exertion required for identification, enhancement of accuracy and consistency and the capability to conduct significant analyses of pollen samples. Such approaches can lead to novel insights and discoveries across various fields [5,6]. In recent years, deep learning has been extensively employed to optimize efficiency and precision, reduce human labour and minimize potential artifacts [7]. Various fields of research that includes but not limited to Animal Identification [50], Herbal plants classifications [51] utilized the techniques. Among the various deep learning techniques, Convolutional Neural Networks (CNNs) have witnessed a surge in popularity over the last decade. They are renowned for their efficacy in tasks such as object detection, image classification and task recognition. This is due to their robust neural network architecture, which autonomously extracts mid- to high-level features from image datasets, contributing to their widespread utilization [8-10].

Nevertheless, CNNs have inherent limitations, most notably in capturing the fine-grained textural details necessary for differentiating visually similar pollen types. Pollen grains possess complex surface textures and patterns that vary greatly between species, making texture analysis critical for accurate classification. Furthermore, CNNs frequently require large amounts of labelled data for effective training, which can be difficult to obtain due to the labour-intensive nature of data annotation in the context of pollen classification [11,12]. To address these limitations, this study employs Gabor filters in addition to CNNs, as Gabor filters are specifically designed for texture analysis and excel at capturing fine textural details. By using Gabor filters to pre-process pollen images, the enhanced representations are rich in texture information, improving the ability to distinguish between visually similar pollen types. This integration also reduces the amount of data required for CNN training, allowing for more efficient model training and classification [13,14].

The combined approach leverages the strengths of both techniques, improving feature extraction and yielding more robust and accurate pollen classification results. Therefore, the purpose of this research is to investigate the efficacy of combining Gabor filters with Convolutional Neural Networks (GF-CNN) for efficient and accurate pollen classification. We also introduce a new set of pollen data as our contribution to the pollen recognition research.

2. Literature Review

The challenge of automating pollen recognition has been a subject of research for nearly five decades. With the recent advancements in machine learning algorithms for image processing and recognition, significant progress has been made towards resolving this challenge, yet it continues to be an area of considerable interest for researchers [15,48]. In the domain of machine learning, feature extraction is the initial and crucial step. Numerous researchers have focused on specific pollen features such as shape, size, brightness, texture and aperture characteristics [16-18,49]. While these features offer clear semantics, they are not universally applicable across all species. After feature extraction, various classification methods are employed and many studies have utilized standard machine learning techniques, achieving accuracy rates ranging from 77 to 99% [19-23].

Several researchers have used scanning electron microscopes (SEM) to produce high-quality images, enabling the extraction of numerous features that streamline the classification task [21]. However, it is important to note that SEM equipment is substantially more expensive—at least 15 times—than light microscopes, making it less accessible for many research facilities. Additionally, some studies have utilized z-stacks of multifocal images of individual pollen grains for classification [20,21]. While effective and leading to high recognition accuracy, this approach requires a substantial number of pollen images, making it labour-intensive unless automated. As a result, automated recognition systems have increased the demand for manual pollen processing with microscopes.

The ASTHMA project, as reported by [24-26] and Chudyk *et al.,* [19], achieved success rates ranging from 77 to 100% when dealing with datasets containing 4 to 12 distinct pollen species. Other researchers, such as Khanzhina [27], Chen *et al.,* [16] and Nguyen *et al.,* [28], have experimented with adding features designed to represent specific pollen characteristics, resulting in improved recognition rates. Furthermore, Kaya *et al.,* [29] relied solely on palynological characteristics, including the lengths of the polar axis, equatorial axis, colpus, exine and others.

Ronneberger *et al.,* [30] introduced a unique approach by utilizing 3D image features tailored for the classification of pollen obtained through confocal microscopy. Their work encompassed 26 species and yielded a remarkable recognition rate of 99.2%. Daood *et al.,* [31] leveraged CNNs combined with SEM pollen images to classify pollen, achieving a recognition rate of 95% across 30 different pollen species. Sevillano *et al.,* [32] presented an illustrative case of pollen classification using a deep convolutional neural network on the POLEN23E image dataset, which comprises 805 high-quality bright-field microscope images representing 23 distinct pollen types found in the Brazilian grassland [33]. Impressively, their model achieved classification accuracy exceeding 97%. Achieving a 97% accuracy rate on a 23-class problem is a significant accomplishment, especially given the number of taxa involved. This stands as one of the most successful documented attempts at automating pollen analysis within the existing literature.

Gabor filters have proven to be a successful method for feature extraction in the context of pollen classification, as demonstrated in studies by Chudyk *et al.,* [19] and Daood *et al.,* [31]. Recent efforts have been made to integrate Gabor harmonics into CNNs to reduce parameter numbers and equip CNNs with orientation and frequency selectivity. For instance, Hosseini *et al.,* [34] incorporated supplementary Gabor features as inputs in CNN-based classification, resulting in improved outcomes. Yao *et al.,* [35] reported elevated recognition rates through the pretraining of CNNs with Gabor features before fine-tuning. Comparable strategies have been documented in previous studies [36,37]. In the field of remote sensing, Chen *et al.,* [38] introduced Gabor features obtained from the initial principal components into CNNs for hyperspectral imaging (HSI) classification, while Shi *et al.,* [39] enhanced CNN features by integrating Gabor features for ship classification, illustrating the capability of Gabor features to augment CNN performance.

Another emerging trend involves the manipulation of specific layers or kernels within CNNs employing Gabor filters. For instance, Jiang *et al.,* [40] opted to replace the kernels in the initial layer of a CNN with a set of Gabor filters characterized by predefined orientation and spatial frequencies. These first-layer Gabor filters can be either static, as detailed in a prior study by Calderon *et al.,* [41] or they can be adjusted individually at each kernel element, as demonstrated in another study by Chang *et al.,* [42], where Gabor filters were utilized for the initialization process. To streamline the training process, Sarwar *et al.,* [43] substituted some kernels in intermediate layers with fixed Gabor filters, resulting in notable enhancements in performance. However, in these tasks, Gabor filters are generally handcrafted with empirically set parameters that remain constant throughout the learning process, suggesting that Gabor computation does not have a substantial impact on CNN learning in existing Gabor-related CNNs.

While many approaches to pollen recognition have been explored, there remains a need for more efficient integration of Gabor filters within CNNs to address certain limitations. This research gap presents an opportunity to improve CNN performance and adaptability for pollen classification by developing a methodology such as GF-CNN, which optimally combines Gabor filters with deep learning and enables the network to learn Gabor features dynamically, potentially leading to superior pollen recognition results.

3. Methodology – Gabor Filters with Convolutional Neural Networks (GF-CNN)

3.1 Datasets

This study utilized two distinct datasets, namely the Malaysian Pollen Dataset (MPD) and the New Zealand Pollen Dataset (NPD), to validate the efficiency and accuracy of the proposed GF-CNN model in classifying pollen grains from diverse geographical and botanical contexts. The MPD was collected from various locations in Terengganu, Malaysia and comprises 40 classes. Each class within the MPD includes over 350 images, accounting for both original and augmented images. The NPD, on the other hand, was collected from 32 native plant species in New Zealand, consisting of a total of 12,516 images representing these 32 pollen classes [44].

Fig. 1. Sample of Malaysian pollen dataset (MPD)

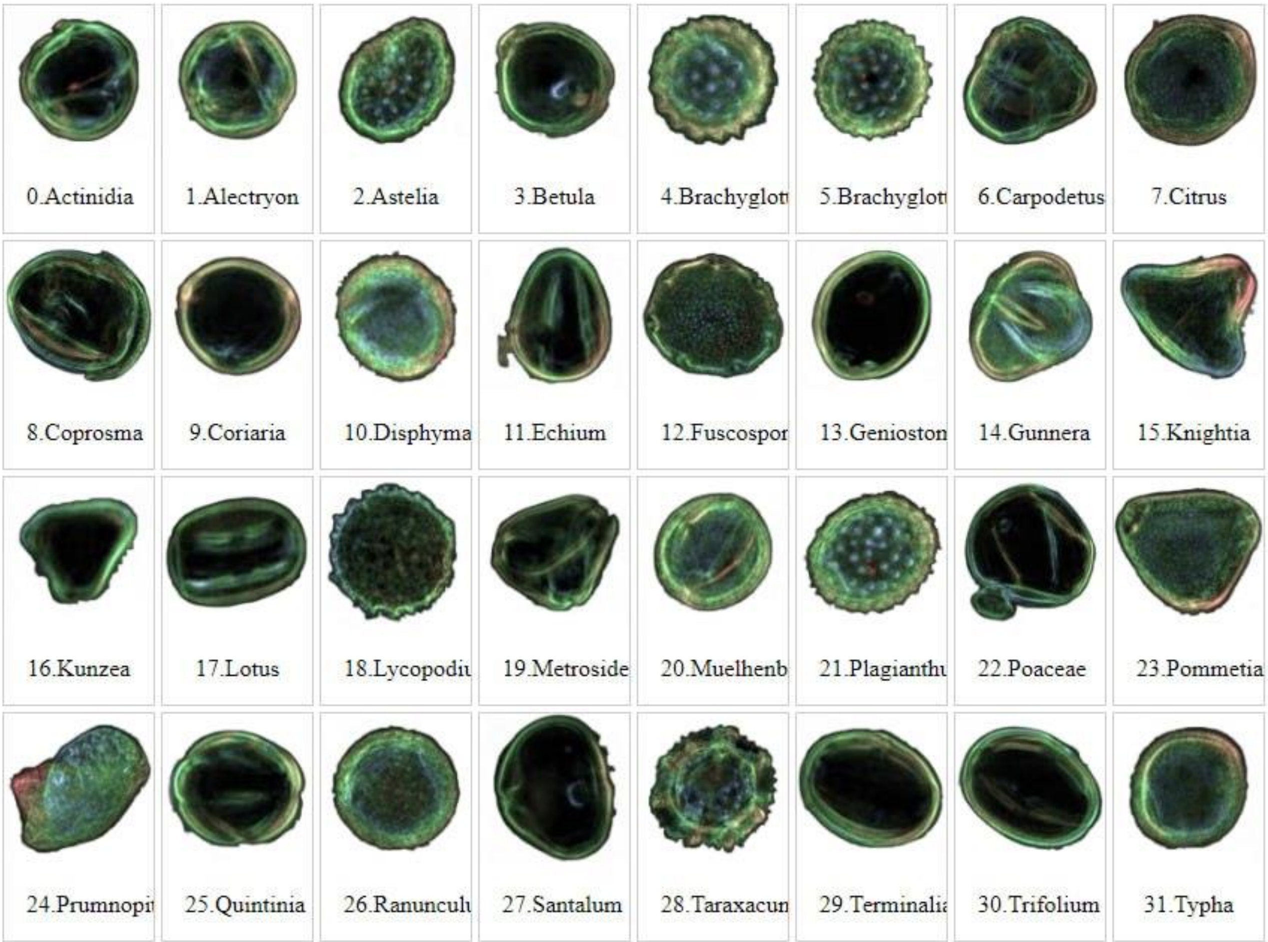

Fig. 2. Sample of New Zealand pollen dataset (NPD)

3.2 Data Preparation and Preprocessing

The acquired images underwent a series of pre-processing steps designed to standardize the input and optimize the feature extraction capabilities of the Gabor filters. These pre-processing steps included resizing, which ensured consistency and interoperability across pollen images and background noise reduction, aimed at minimizing the influence of extraneous elements such as background clutter, illumination variations and noise artifacts. Additionally, the images were converted to grayscale to reduce the impact of colour variations, thereby enhancing the subsequent texture analysis. Following these pre-processing steps, Gabor filters were applied to accentuate the texture-specific features inherent to each pollen type, resulting in feature-enhanced images that were then ready for classification via the CNN model. The overall research methodology is illustrated in Figure 3, while Figure 4 and 5 depict the distribution of images in the Malaysian Pollen Dataset and New Zealand Pollen Dataset, respectively.

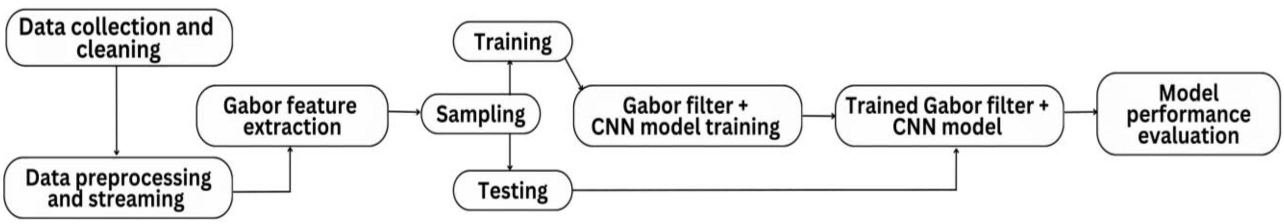

Fig. 3. Research methodology flowchart

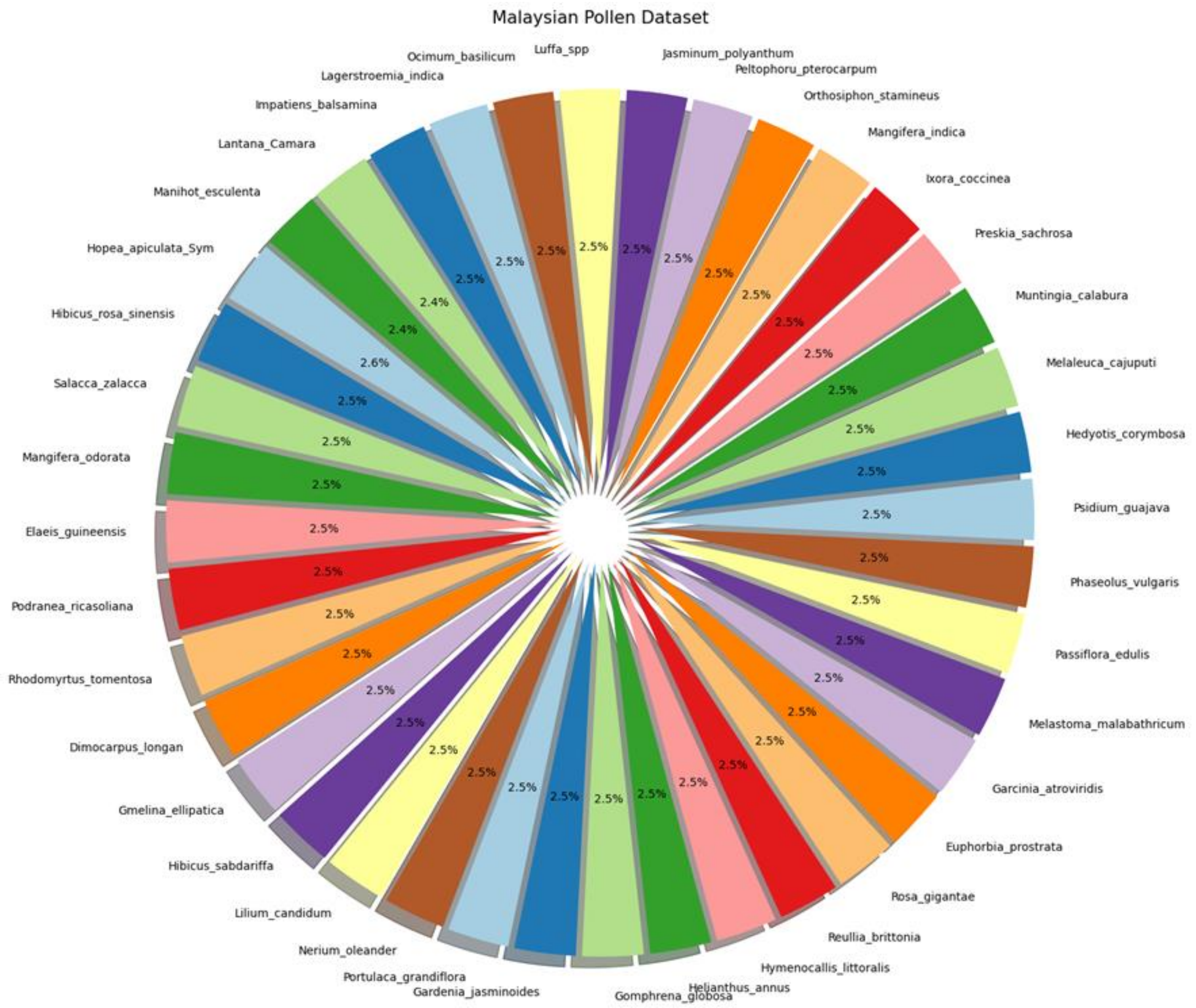

Fig. 4. Distribution of Malaysian pollen dataset images

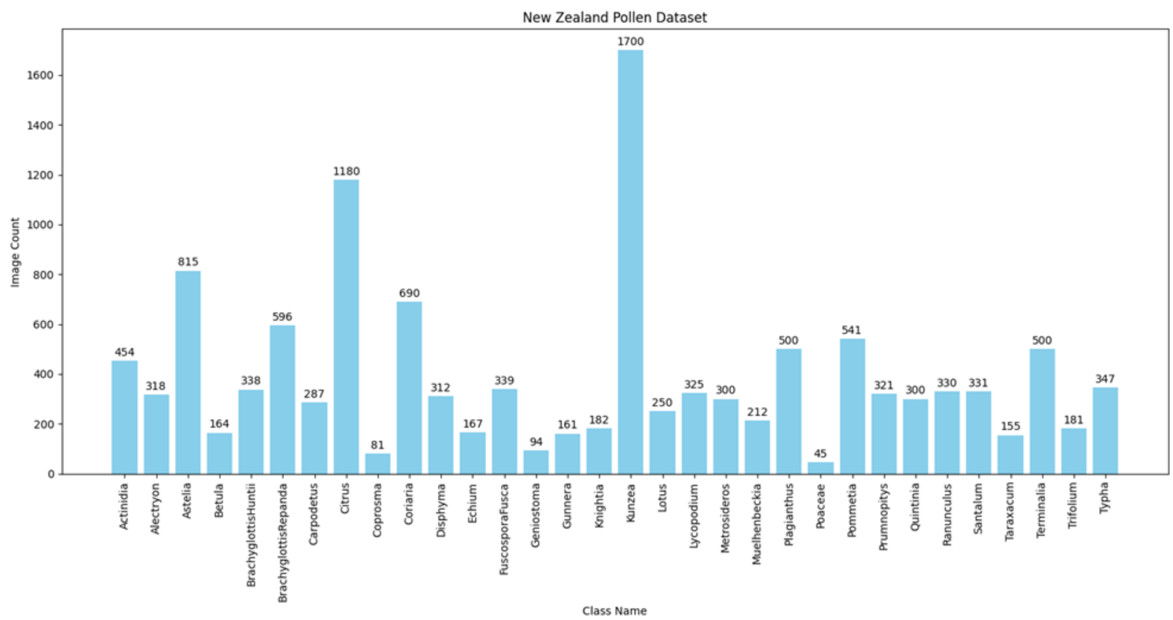

Fig. 5. Distribution of New Zealand pollen dataset images

3.3 Feature Extraction

The normalized images were subjected to filtering using a set of Gabor filters. Four different orientation settings and two distinct wavelength parameters were applied, resulting in a collection of distinct filtered images derived from each original image. Following this, the filtered images were down-sampled using bicubic interpolation to achieve pixel-level resolution. This process produced a feature vector for each original image, with the length of the vector corresponding to the number of pixels.

To further enhance the representation, an additional feature related to the size of each pollen grain in a polar view was introduced. This feature was assigned a weight factor, which was determined by the frequency of occurrences of the same pollen size within the dataset. The weight factor was configured as a specified percentage of the feature vector's dimension. The modified Gabor filter used for feature extraction in this research is represented in Eq. (1), while Figure 6 illustrates the methodology for feature extraction using the Gabor filter.

$$Gabor(x,y) = \cos(2\pi x\lambda_0)\, exp\left(-\frac{x^2}{2\sigma^2} - \frac{\Upsilon^2 y^2}{2\sigma^2}\right) \tag{1}$$

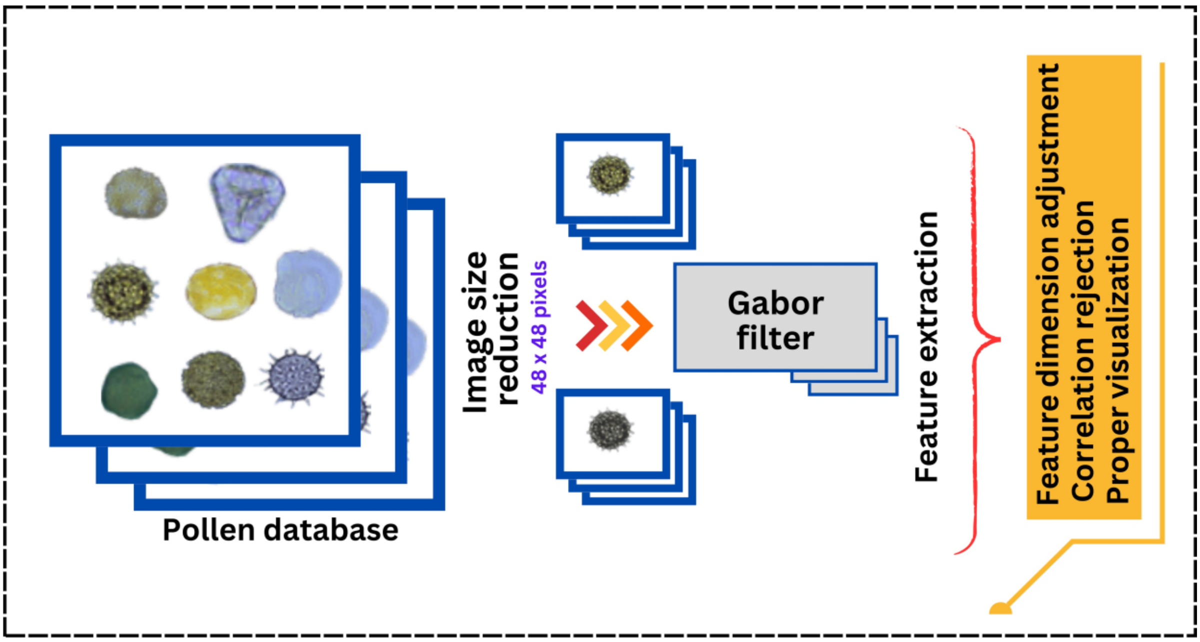

Fig. 6. Feature extraction by Gabor filter

Where: *x, y* represents spatial coordinates, λ_0 is the patterns characteristics scale, σ is standard deviation, Υ represent spatial aspect ratio. Table 1 shows the parameters for the function to generate Gabor Filter from a pollen image.

Table 1
Parameters for Gabor filters

Parameter	Details	Values
Frequency	The spatial frequency of the cosine factor	0.4, 0.6, 0.8
Sigma	The Gaussian envelope's standard deviation	1, 2, 3
Theta	Orientation of the normal to the parallel stripes of a Gabor function	0, 45, 90, 135 degrees
Phi	The phase offset	0, 90 degrees

Figure 7 illustrates a random pollen image and its corresponding Gabor Filters output image.

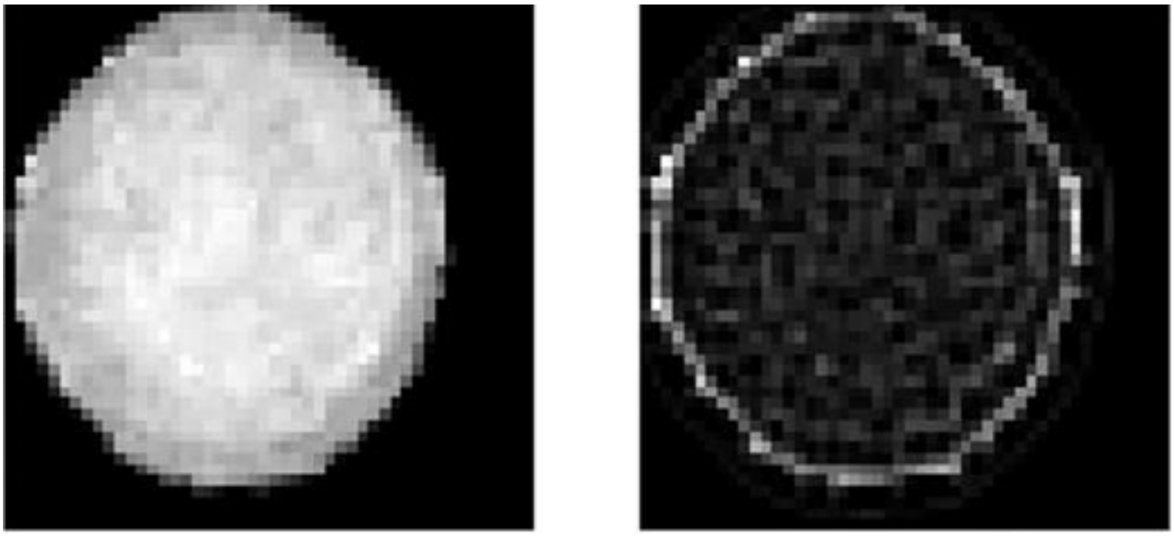

Fig. 7. Output of original pollen image (left) and corresponding Gabor filter image (right)

3.4 Pollen Classification

CNNs, also known as ConvNets, were first introduced in the 1990s, with a significant contribution made by LeCun *et al.,* [45] in 1998. However, CNNs gained widespread popularity and recognition following the groundbreaking success of AlexNet in the 2012 ImageNet competition [46]. Since then, numerous modifications and variations of CNNs have been developed, though many of these adaptations have not been extensively applied to the classification of scattered images of airborne particles of biological origin.

In the proposed GF-CNN architecture, the extracted Gabor features serve as the input for the CNN model, which comprises multiple layers specifically designed for the hierarchical extraction of high-level features from the input images. The network is trained using a subset of the labelled dataset, with performance validated through cross-validation techniques. The architecture is optimized for grayscale images with a default resolution of 48 x 48 pixels. The architecture begins with an input layer, followed by a convolutional layer containing 6 filters, each with a size of 5 × 5. This layer employs same padding, ensuring that the output spatial dimensions remain unchanged after convolution. Subsequently, a MaxPooling layer with a 2 × 2 pool size is applied, effectively halving the spatial dimensions.

This pattern continues with subsequent layers. The model incorporates a second convolutional layer with 16 filters of size 5 × 5, followed by another MaxPooling operation. A third convolutional layer is then introduced, equipped with 64 filters of size 3 × 3, accompanied by an additional MaxPooling layer. After the convolutional operations, the architecture flattens the resulting 3D tensor into a 1D vector, which is then processed by a fully connected layer comprising 128 neurons, activated by a Rectified Linear Unit (ReLU) function. To mitigate the risk of overfitting, a dropout layer is included, randomly setting 50% of its input data units to zero during training. The final layer is a dense layer with 32 neurons, utilizing a SoftMax activation function, which categorizes the input images into one of 32 and 40 possible classes for the NPD and MPD datasets, respectively. The model's working procedure is detailed in Algorithm 1, as shown in Table 2, while Figure 8 and Figure 9 illustrate the architecture employed for both the MPD and NPD datasets.

Table 2
Algorithm 1: Pollen image classification using CNN

```
Procedure CreatePollenModel (input_shape)
 if input_shape is None then
   input_shape ← (48, 48, 1)
 end if
 Initialize model as Sequential ()
 Add Input layer of shape = input_shape ← Convolutional Blocks
 for filters, kernel_size in [(6, (5,5)), (16, (5,5)), (64, (3,3))] do
   model.add (Conv2D (filters, kernel_size, activation = 'ReLU'))
   model.add (MaxPool2D(2, 2))
 end for
 Flatten the output
 model.add(Dense(128, activation='ReLU'))
 model.add(Dropout(0.5))
 model.add(Dense(40, activation='softmax')) ← Dataset 1
 model.add(Dense(32, activation='softmax')) ← Dataset 2
 return model
end procedure
```

3.5 Performance Evaluation

The performance of the proposed method was assessed using precision, as described in Eq. (2), recall, as outlined in Eq. (3) and the F1-score, according to Eq. (4). In these equations, TP represents true positives, TN denotes true negatives, FP corresponds to false positives and FN indicates false negatives. High precision and recall values, as demonstrated by the F1-score in Eq. (4), reflect the model's effectiveness in minimizing both false positives and false negatives, thereby enhancing its overall reliability and accuracy [47].

$$Precision = \frac{\sum(TP)}{\sum(TP)+\sum(FP)} \tag{2}$$

$$Recall = \frac{\sum(TP)}{\sum(TP)+\sum(FN)} \tag{3}$$

$$F1 - score = \frac{2*recall*precision}{recall+precision} \tag{4}$$

The F1-score provides a comprehensive evaluation by combining precision and recall into a single metric. A high F1 score indicates that the model has effectively minimized both false positives and false negatives, thereby demonstrating the model's reliability and consistency across these metrics. In our experiments, precision, recall and F1 scores were calculated using weighted averages, which account for the number of true instances in each class. Additionally, the classification model's accuracy was determined by dividing the number of correct predictions by the total number of samples. The effectiveness of the proposed GF-CNN model was then compared with other machine learning methods, including Random Forest (RF), Support Vector Machine (SVM), AlexNet, Multi-Layer Perceptron (MLP) and Vision Transformer (ViT).

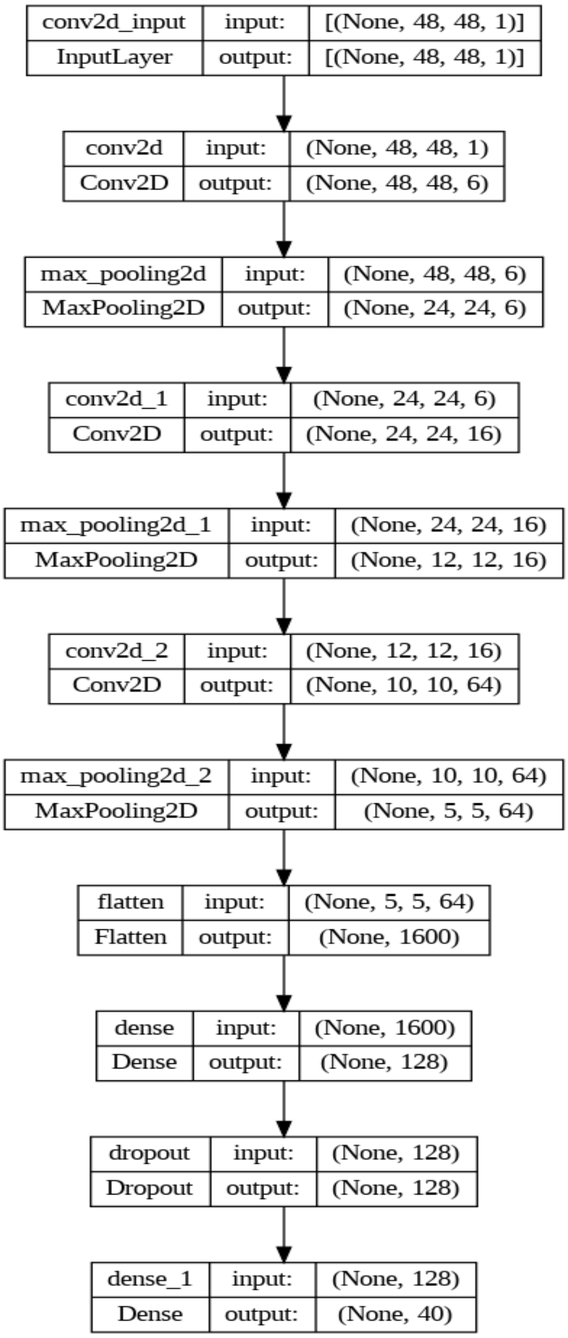

Fig. 8. Architecture for Malaysian pollen

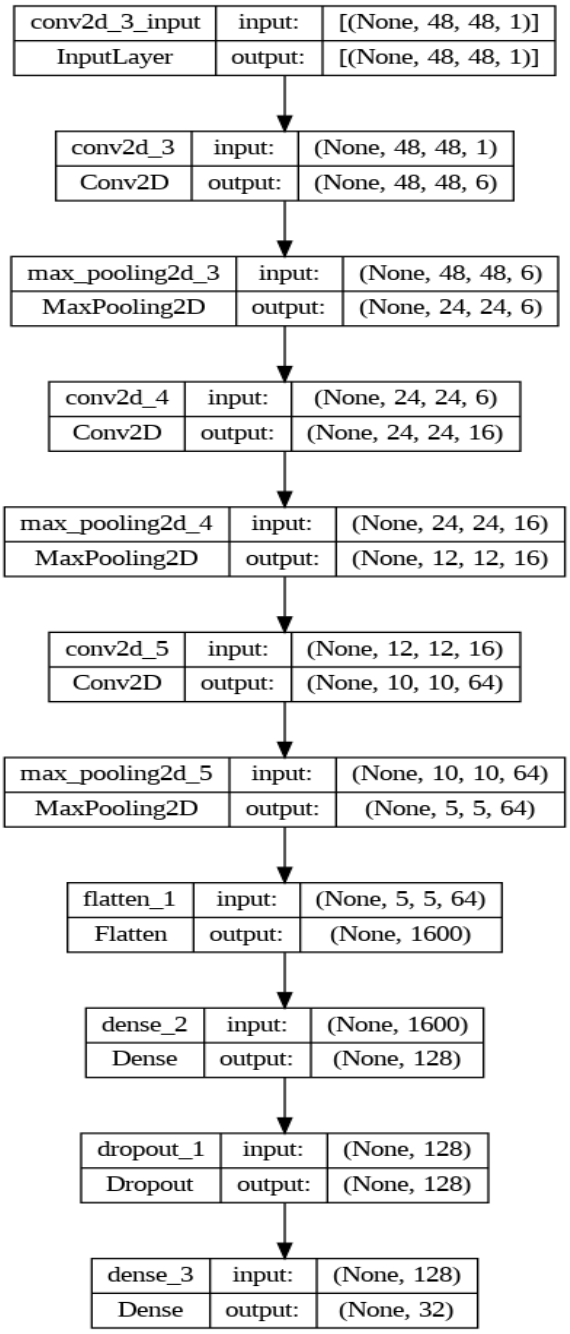

Fig. 9. Architecture for New Zealand pollen

4. Results and Discussion

4.1 Precision Results

According to Table 3, RF is the most accurate method, with a precision of 0.9304 for MPD and an even greater precision of 0.9889 for NPD. With 0.8920 for MPD and 0.9316 for NPD, SVM has decent precision, slightly lower than RF. Deep learning models, like AlexNet, exhibit outstanding accuracy, particularly in NPD. The proposed GF-CNN beats all others, reaching 0.9907 precision for MPD and 0.9930 precision for NPD. These findings highlight the ability of deep learning models, notably GF-CNN, to achieve high-precision pollen classification results across heterogeneous datasets, providing insights for a variety of scientific applications

Table 3
Precision results comparison with other algorithms

Algorithms	Precision results for MPD	Precision results for NPD
RF	0.9304	0.9889
SVM	0.8920	0.9316
AlexNet	0.9510	0.9824
ViT	0.9302	0.9214
MLP	0.9611	0.8901
Proposed GF-CNN	0.9907	0.9930

4.2 Recall Results

According to Table 4, RF has a recall of 0.9824 for MPD and 0.9822 for NPD, demonstrating its robustness in both datasets. SVM produces consistent recall outcomes, behind RF by 0.9263 for MPD and 0.9402 for NPD. AlexNet excels in NPD, with a recall of 0.9846, but struggles in MPD, with a recall of 0.8940. The Vision Transformer (ViT) provides consistent recall performance, but the MLP gets a great 0.9723 in MPD but varies with 0.9564 in NPD. The proposed GF-CNN outperforms all others in terms of recall, obtaining 0.9909 for MPD and 0.9889 for NPD, demonstrating its ability to properly detect positive cases across varied datasets. These recall results highlight the ability of deep learning models, notably the proposed GF-CNN, to achieve high-accuracy results for pollen categorization, which has implications in a variety of scientific domains.

Table 4
Recall results comparison with other algorithms

Algorithms	Precision results for MPD	Precision results for NPD
SVM	0.9263	0.9402
AlexNet	0.8940	0.9846
ViT	0.9703	0.9756
MLP	0.9723	0.9564
Proposed GF-CNN	0.9909	0.9889

4.3 F1-Score Results

The F1-Score scores for pollen categorization algorithms on the MPD and the NPD provide important information about their overall accuracy, as shown in Table 5. RF has excellent F1-Scores, with 0.9912 for MPD and 0.9350 for NPD, demonstrating its ability to strike a compromise between precision and recall. SVM performs consistently in both datasets, with F1-scores of 0.9835 for MPD and 0.9862 for NPD. AlexNet's capacity to balance precision and recall varies, with a greater F1-Score of 0.9532 for NPD and a lower 0.9201 for MPD. The Vision Transformer (ViT) maintains a solid equilibrium with F1-scores of 0.9842 for MPD and 0.9830 for NPD, whereas the MLP succeeds in MPD with a score of 0.9771 but struggles in NPD with a score of 0.8924. The proposed GF-CNN has the greatest F1 scores, showing its excellent ability to attain a balance of precision and recall in both datasets, emphasizing its promise for high-accuracy pollen categorization.

Table 5
F1-Score results comparison with other algorithms

Algorithms	Precision results for MPD	Precision results for NPD
RF	0.9912	0.9350
SVM	0.9835	0.9862
AlexNet	0.9201	0.9532
ViT	0.9842	0.9830
MLP	0.9771	0.8924
Proposed GF-CNN	0.9999	0.9823

4.4 Models Accuracy

The accuracy of the algorithms, a fundamental metric, is detailed in Table 6 and highlights their ability to correctly classify pollen samples. RF stands out with an impressive accuracy of 96.57% for the MPD and an exceptional 99.20% for the NPD. SVM also demonstrates consistent accuracy, though it slightly lags behind RF, achieving 89.56% for MPD and 98.43% for NPD. AlexNet, while showing a lower accuracy of 74.64% for MPD, excels in NPD with an outstanding 99.12% accuracy. The Vision Transformer (ViT) maintains consistent performance, with 94.73% accuracy for MPD and 98.20% for NPD. The MLP performs well across both datasets, recording 94.73% for MPD and 98.54% for NPD. Notably, the proposed GF-CNN achieves the highest accuracy in both datasets, with 99.85% for MPD and 99.43% for NPD, showcasing its robustness in reliably classifying pollen samples across diverse datasets. These findings underscore the potential of deep learning models, particularly the proposed GF-CNN, for achieving high-accuracy pollen categorization, with significant implications for a broad range of scientific applications.

Table 6
Recall results comparison with other algorithms

Algorithms	Precision results for MPD (%)	Precision results for NPD (%)
SVM	89.56	98.43
AlexNet	74.64	99.12
ViT	94.73	98.20
MLP	94.73	98.54
Proposed GF-CNN	99.85	99.43

4.5 Confusion Matrix

The confusion matrix for the MPD, as shown in Figure 10, provides a detailed illustration of the classification accuracy across different categories. The heatmap of classification results for the MPD dataset is represented, with darker squares indicating higher frequencies of correct predictions. In the MPD confusion matrix, the diagonal line represents the number of correct predictions, while the off-diagonal elements highlight instances of misclassification. The numbers 0-39 correspond to the indices of pollen classes, with sample images of each class available in Figure 1. The vertical axis represents the true values, while the horizontal axis denotes the predicted values.

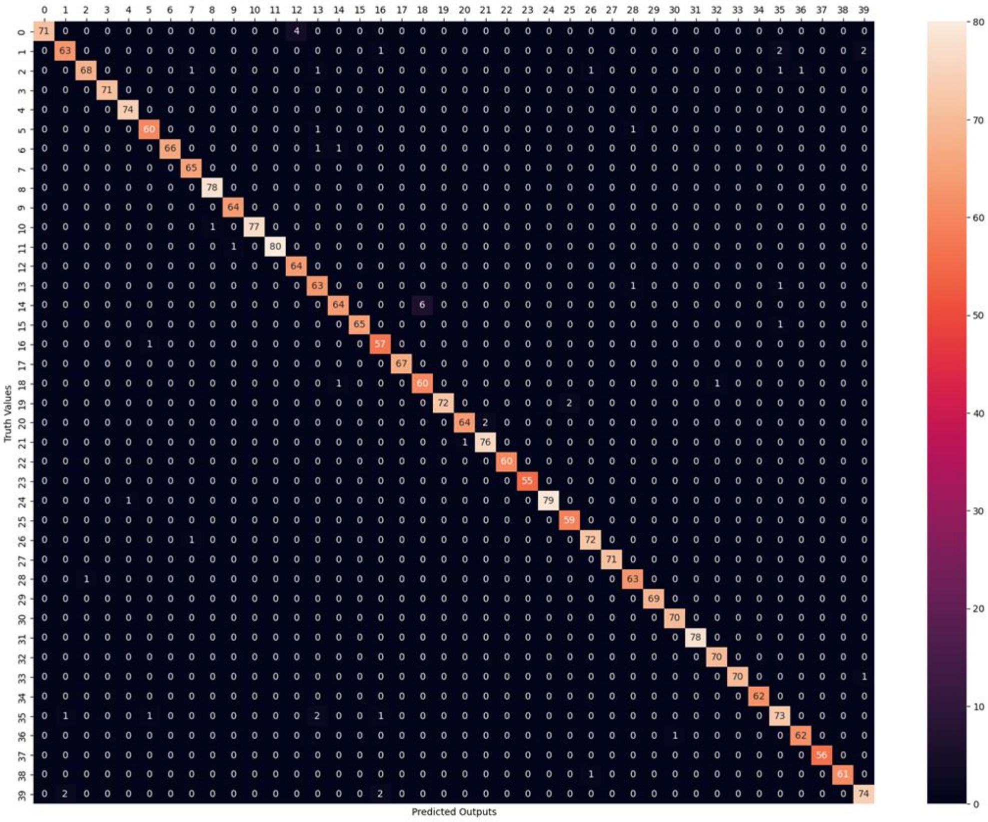

Fig. 10. Confusion matrix with Malaysian pollen dataset

Similarly, Figure 11 presents the confusion matrix for the NPD as classified by the proposed GF-CNN method. This visualization of classification outcomes for the NPD dataset also uses a heatmap, where darker squares indicate a higher frequency of correct predictions. In the NPD confusion matrix, the diagonal line shows the number of correct predictions, with off-diagonal elements representing misclassifications. The numbers 0-31 correspond to the indices of pollen classes, with sample images available in Figure 2. As with the MPD, the vertical axis represents the true values and the horizontal axis indicates the predicted values.

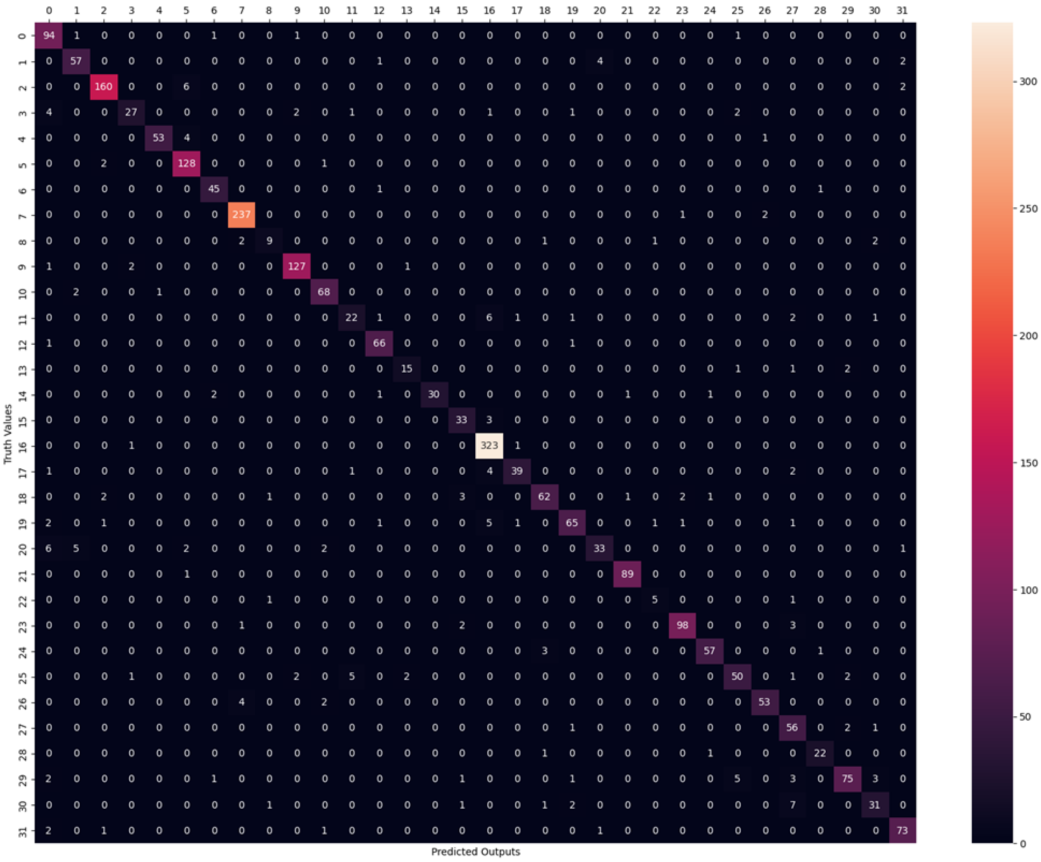

Fig: 11. Confusion matrix with New Zealand pollen dataset

5. Conclusions

The inherent complexity and critical importance of pollen grain classification underscore the necessity for accurate and efficient techniques. Traditionally, the reliance on manual methods has presented numerous challenges, ranging from labour-intensive processes to the inherent subjectivity involved in the analysis. This research demonstrates that integrating Gabor filters with CNNs offers a transformative solution, marking a significant shift from conventional methods to a modern, automated and highly effective approach. The analysis conducted on two distinct pollen datasets validated the efficacy of the integrated GF-CNN model, which not only demonstrated superior classification accuracy but also effectively captured the nuanced, texture-based distinctions inherent to diverse pollen species. This advancement in precision has substantial implications across various scientific disciplines, including botany, ecology, environmental monitoring and climate change analysis.

Furthermore, the successful fusion of Gabor filters for feature extraction with CNNs for deep learning introduces a methodology with potential applications far beyond pollen analysis. Areas such as medical diagnostics, agricultural bioengineering and forensic science could benefit from this approach, highlighting the broad-reaching ramifications of this research. As technological advancements continue to reshape the landscape of scientific inquiry, the adoption of integrated models like GF-CNN exemplifies the future of research—a blend of domain-specific knowledge with computational prowess, driving us toward profound and impactful discoveries.

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