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Development of an Enhanced Convolutional Neural Network for Face Mask-wearing Identification system

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Abstract

Face mask-wearing identification systems leverage technology to automatically detect whether individuals are wearing face masks in public spaces. Identifying individuals wearing face masks remains a significant challenge for Convolutional Neural Networks (CNNs) due to the obstruction and occlusion of critical facial features, coupled with variations in mask types, limited datasets, and ethical concerns. However, many existing CNN techniques suffer from difficulty in selecting optimal hyperparameters, which constrain their accuracy, interpretability, and computational efficiency. Hence, this research developed a Pelican Optimization Algorithm (POA)-based Convolutional Neural Network (POA-CNN) framework to optimize CNN hyperparameters, thereby enhancing the model's generalization capability and improving recognition accuracy. Face mask-wearing and non-mask-wearing image datasets were acquired from a publicly available Kaggle dataset comprising 3,059 images across two classes. Image preprocessing was performed using Contrast Limited Adaptive Histogram Equalization (CLAHE) to normalize contrast and enhance image quality prior to analysis. The Pelican Optimization Algorithm (POA) was employed to optimize critical CNN hyperparameters, including weights, number of layers, filter sizes, and number of filters, resulting in the developed POA-CNN model. The POA-CNN framework was used for feature extraction, training, and face mask-wearing identification and was implemented in MATLAB R2023a. The performance of the developed POA-CNN model was evaluated using accuracy, precision, sensitivity, specificity, false positive rate, and identification time and compared with the conventional CNN. The POA-CNN achieved an accuracy of 96.54%, precision of 96.95%, sensitivity of 96.95%, specificity of 96.00%, false positive rate of 4.00%, and an identification time of 43.06 seconds. In comparison, the conventional CNN achieved an accuracy of 94.08%, precision of 94.67%, sensitivity of 94.91%, specificity of 93.00%, false positive rate of 7.00%, and an identification time of 65.76 seconds. The developed POA-CNN model outperformed the conventional CNN by providing higher classification accuracy, precision, sensitivity, and specificity while reducing the false positive rate and computational time through effective optimization of CNN hyperparameters. Therefore, the POA-CNN model is suitable for real-time face mask-wearing identification applications due to its improved recognition performance and computational efficiency.

Keywords: *Face Mask Detection, Convolutional Neural Network, Face Recognition, Deep Learning, Machine learning, Metaheuristic Optimization, Pelican Optimization Algorithm, Hyperparameter Optimization.*

1. Introduction

Face mask-wearing identification has become an important application of computer vision and artificial intelligence, particularly in public health surveillance, intelligent access control, and security monitoring. The COVID-19 pandemic emphasized the need for automated systems capable of identifying individuals wearing face masks in crowded environments such as airports, hospitals, shopping malls, educational institutions, and transportation terminals, where manual inspection is impractical. Automated face mask identification systems provide rapid, consistent, and contactless monitoring, making them suitable for large-scale surveillance applications. Among deep learning techniques, Convolutional Neural Networks (CNNs) have demonstrated remarkable success in image classification and object recognition because of their ability to automatically learn hierarchical feature representations from image data. Consequently, CNN-based approaches have become the dominant solution for face mask-wearing identification. However, CNN performance is highly dependent on appropriate hyperparameter configuration. Manually determining suitable hyperparameters is computationally expensive because of the large search space involved, while inappropriate configurations often lead to poor convergence, reduced generalization, and suboptimal classification performance. To improve CNN performance, numerous optimization techniques have been investigated. Metaheuristic optimization algorithms have attracted considerable attention because of their ability to efficiently search complex, high-dimensional solution spaces through a balance between exploration and exploitation. Despite these advantages, existing optimization approaches may suffer from premature convergence, high computational cost, or an inadequate balance between global exploration and local exploitation, thereby limiting the effectiveness of CNN hyperparameter optimization. Recent studies have reported impressive face mask detection performance using deep learning models; however, several challenges remain. Existing methods frequently rely on manually selected or default hyperparameter settings, are evaluated on limited datasets, or exhibit a trade-off between classification accuracy and computational efficiency. Furthermore, robust optimization strategies capable of improving CNN learning capability and generalization remain an active research problem.

To address these limitations, this study proposes an Improved Pelican Optimization Algorithm (IPOA) to enhance CNN performance for face mask-wearing identification. The proposed optimization approach is employed during CNN training to improve the selection of network parameters, thereby enhancing learning capability, generalization performance, and identification accuracy. The effectiveness of the proposed IPOA is evaluated using a publicly available face mask dataset and validated through standard performance metrics, including false positive rate, sensitivity, specificity, precision, F1-score, classification accuracy, and identification time.

The main contributions of this study are summarized as follows:

- An Improved Pelican Optimization Algorithm (IPOA) is proposed to enhance the optimization capability of the conventional Pelican Optimization Algorithm.
- The proposed IPOA is employed to optimize a CNN for face mask-wearing identification.
- The effectiveness of the proposed optimization approach is validated using a publicly available dataset through comprehensive experimental evaluation and comparison with the conventional CNN.

The remainder of this paper is organized as follows. Section 2 reviews related studies on face mask-wearing identification and optimization techniques. Section 3 presents the proposed methodology. Section 4 discusses the experimental results and performance evaluation. Finally, Section 5 concludes the paper and outlines future research directions.

2 Related Work

2.1 Deep Learning-Based Face Mask-Wearing Identification

Deep learning has become the dominant approach for face mask-wearing identification because of its ability to automatically extract discriminative image features. CNN-based models have demonstrated high recognition accuracy across various datasets. For instance, Chavda et al. (2021) developed a two-stage CNN architecture for detecting proper and improper face mask usage in CCTV environments, whereas Christa et al. (2021) employed MobileNet integrated with TensorFlow, Keras, and OpenCV to achieve approximately 99% accuracy. Similarly, Huang (2021) proposed a cascade CNN capable of simultaneously detecting faces and masks, although the method exhibited false positives in complex backgrounds. Other lightweight deep learning approaches based on YOLOv5 and MobileNetV2 have also reported competitive performance while improving computational efficiency (Ieansaard et al., 2021; Nayak and Manohar, 2021; Sajid, 2021). Despite these encouraging results, model performance remains sensitive to image quality, environmental conditions, and network parameter configuration.

2.2 CNN Hyperparameter Optimization

The performance of Convolutional Neural Networks (CNNs) depends not only on network architecture but also on the selection of appropriate hyperparameters, which influence convergence, classification accuracy, computational complexity, and model generalization. Although recent CNN-based face mask-wearing identification systems have achieved promising results, their effectiveness remains highly dependent on suitable parameter configuration. For example, CNN-based approaches proposed by Chavda et al. (2021), Christa et al. (2021), Huang (2021), Ieansaard et al. (2021), Lin et al. (2021), and Nayak and Manohar (2021) demonstrated high identification accuracy under different experimental settings but exhibited limitations related to environmental conditions, computational efficiency, and parameter selection.

To improve CNN performance, researchers have increasingly employed metaheuristic optimization algorithms to search for optimal network configurations. Among these, the Pelican Optimization Algorithm (POA) has shown promising performance through adaptive exploration and exploitation mechanisms (Trojovský and Dehghani, 2022), while the Zebra Optimization Algorithm (ZOA) has demonstrated effective search capability for solving complex optimization problems (Trojovská et al., 2022). Nevertheless, existing optimization methods may still experience premature convergence and insufficient balance between exploration and exploitation, limiting CNN performance. These challenges motivate the development of improved optimization strategies for CNN-based face mask-wearing identification.

2.3 Research Gap

Recent advances in deep learning have significantly improved the performance of face mask-wearing identification systems. Nevertheless, existing CNN-based approaches remain highly dependent on appropriate hyperparameter selection, which directly influences learning capability, classification accuracy, and computational efficiency. Although several optimization techniques have been applied to improve CNN performance, many still encounter challenges such as premature convergence, high computational complexity, and an inadequate balance between exploration and exploitation, thereby limiting their effectiveness in solving complex optimization problems. Furthermore, most existing studies primarily emphasize improvements in CNN architectures or detection frameworks, with relatively limited attention given to developing robust optimization strategies for enhancing CNN learning performance. Consequently, there remains a need for an effective optimization approach that can improve CNN hyperparameter optimization while maintaining high identification accuracy and computational efficiency. This study addresses this gap by proposing an Improved Pelican Optimization Algorithm (IPOA) for CNN-based face mask-wearing identification.

3. Materials and Methods

3.1 Research Framework

In developing an automatic face mask-wearing identification system using Improved Pelican Optimization based Convolutional Neural Network algorithm (IPOA-CNN), the following stages are involved in the methodology.

i. Acquisition of face dataset with mask-wearing was obtained from Ladoke Akintola University of Technology and from publicly available dataset.

ii. Pre-processing of the acquired dataset was done by normalizing the image contrast and increase the quality of the images using Contrast Limiting Adaptive Histogram Equalization (CLAHE).

iii. IPOA was formulated by introducing the exploitation and exploitation ability of zebra optimization algorithm and roulette wheel selection method instead of random selection into the standard POA.

iv. Use IPOA to select CNN hyperparameters such as weights, number of layers, filter size and number of filters.

v. Feature Extraction, Training and Identification of face mask-wearing was achieved by using Improved-Pelican Optimized based Convolutional Neural Network (IPOA-CNN).

vi. Evaluation of the predictive performance of IPOA-CNN, POA-CNN and CNN technique for face mask-wearing was done using false positive rate, sensitivity, specificity, accuracy, precision and identification time.

The overall architecture and operational flow of these steps are illustrated in the diagram

in Figure 1:

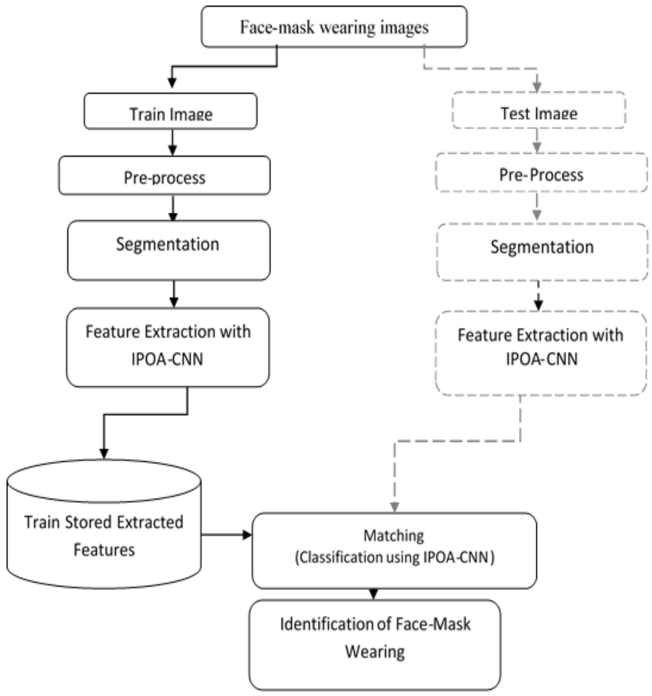


Figure 1: Flow Diagram of the Identification Process using IPOA-CNN

3.2 Dataset Description

A face mask-wearing and no mask-wearing of 3,059 number of images from www. Kaggle.com (face-mask-dataset, 2022) which belong to two classes face with mask and without mask was used in this study. Seventy percent (2,142) of the dataset was used for training and thirty percent (917) of the dataset was used for testing using random sub-sampling cross-validation method.

3.3 Image Preprocessing

Pre-processing contains sequential operations. Image pre-processing has to do with actions such as image brightness, contrast alteration, image scaling, filtering, cropping and other operations that help in the enhancement of images. In this phase, pre-processing was carried out by converting the colored images into grayscale, cropping the image and normalizing of face vectors by computing the average face vector and deducting average face from each face vector. This was done to remove noise from the face images (Saravanan, 2010; Tan et al., 2012, Barnouti, 2016).

4. Results and Discussion

4.1 Result of the Developed Model

The face mask identification system was developed and trained using a dataset consisting of a total of 3,059 images, of which 1,500 belonged to the "no mask" class and 1,559 belonged to the "face mask" class. To ensure a balanced evaluation of the proposed models, the dataset was split into 70% for training and 30% for testing, resulting in 2,366 images used for training and 693 images for testing. The division of data was carried out using the random subsampling cross-validation method, which enhances the reliability of the results by ensuring that different subsets of the dataset contribute to both the training and testing phases. This approach prevents overfitting and improves the model's ability to generalize across unseen data. The choice of a balanced dataset, coupled with this validation method, provides a strong foundation for evaluating the performance of CNN and POA-CNN

The implementation of the system was further demonstrated through a graphical user interface (GUI), which enables the processes of training, testing, and identifying face mask usage to be visualized. As shown in Figure 2, the training interface illustrates the process of feeding images into the system, applying threshold values, and configuring options to choose between CNN and POA-CNN techniques. Similarly, Figure 3 presents the testing interface, where unseen images are evaluated, and the corresponding classification outputs are displayed. The GUI also integrates essential functionalities such as saving results, threshold plotting, and cropped image thresholding, which provide an interactive means of verifying system performance. This visual representation of the developed system validates its usability and practical implementation for real-world applications.

In addition to offering classification outputs, the developed model demonstrates flexibility and adaptability through its design. The incorporation of adjustable threshold values and interactive display outputs provides a way for users to refine the decision boundaries of the classifier. This adaptability is particularly useful in handling cases where facial occlusions, lighting variations, or partial mask coverings may complicate classification accuracy.

The GUI further allows for the real-time visualization of the classification process, including the display of cropped facial regions and their corresponding confidence scores, providing immediate insight into the model's decision-making. This feature is crucial for debugging and for building user trust in the automated system. Moreover, the ability to switch seamlessly between the CNN and POA-CNN models within the same interface facilitates a direct and efficient comparative analysis without altering the testing environment. The integration of POA within the GUI emphasizes the system's novelty, as it does not only rely on a conventional CNN but also leverages metaheuristic optimization for performance improvement. The results from this developed model serve as a foundation for the subsequent sections where the performance of each technique is analyzed in detail.

Figure 2: Training Interface of the Developed Face Mask Identification System

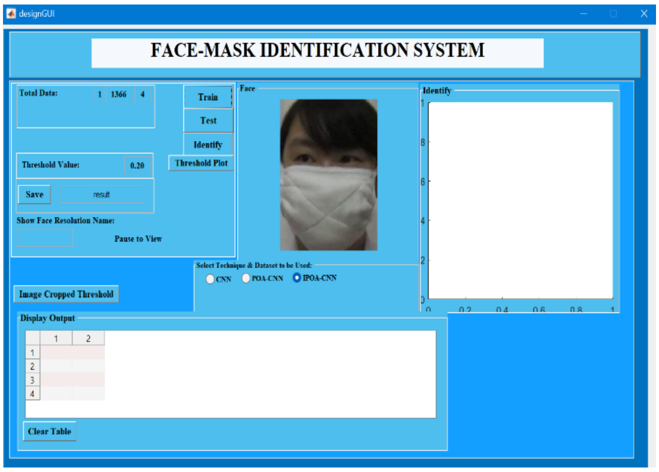


Figure 3: Testing Interface of the Developed Face Mask Identification System.

The hyperparameter tuning of the baseline CNN was carried out to build a reference model before introducing metaheuristic optimization methods. Parameters such as the number of convolutional layers, filter size, number of filters, and initialization weights were defined through preliminary experimentation. The CNN architecture employed three convolutional layers, using filter sizes between 5×5 and 7×7, and filter counts ranging from 32 to 64 to balance complexity and efficiency. The network weights were initialized at 0.41, resulting in a fitness value of 0.9408, as summarized in **Table 3**. This baseline model provided a performance benchmark that reflects the behavior of a conventional CNN without optimization.

The POA-CNN applied the Pelican Optimization Algorithm to refine CNN hyperparameters through iterative exploration of candidate solutions. The algorithm adjusted parameters across the ranges observed in **Table 1**, including weights from 0.1185 to 0.9729, number of layers from 2 to 9, filter sizes between 3×3 and 7×7, and filter counts from 16 to 128. After systematic evaluations, the best configuration identified was six convolutional layers with a 5×5 filter size, 64 filters, and a weight of 0.3629, achieving a fitness value of 0.9723. This configuration shows that POA successfully increased the CNN's performance by identifying effective trade-offs in depth, filter resolution, and weight scaling. These results confirm that POA-CNN significantly improves feature extraction capability and generalization compared to the baseline CNN.

Table 2: CNN Hyperparameters Selection Process with POA

S/N	Weights	Number of Layers	Filter Size	Number of Filters	Fitness Value	Best
1	0.4371	4	5x5	64	0.7993	FALSE
2	0.9556	8	5x5	16	0.7191	FALSE
3	0.7588	6	5x5	16	0.7933	FALSE
4	0.6388	2	5x5	16	0.7976	FALSE
5	0.2404	8	5x5	64	0.9189	FALSE
6	0.2404	3	5x5	16	0.8913	FALSE
7	0.1523	5	3x3	128	0.9662	FALSE
8	0.8796	2	7x7	16	0.8417	FALSE
9	0.641	5	5x5	128	0.7359	FALSE
10	0.7373	7	5x5	128	0.914	FALSE
11	0.1185	3	5x5	128	0.9282	FALSE
12	0.9729	3	5x5	64	0.8684	FALSE
13	0.8492	2	5x5	64	0.9313	FALSE
14	0.2911	3	5x5	64	0.8481	FALSE
15	0.2636	6	7x7	16	0.8568	FALSE
16	0.2651	3	7x7	128	0.8283	FALSE
17	0.3738	5	5x5	64	0.7076	FALSE
18	0.5723	5	7x7	64	0.7324	FALSE
19	0.4888	8	3x3	16	0.7094	FALSE

20	0.3621	5	5x5	64	0.8909	FALSE
21	0.6507	8	3x3	16	0.7943	FALSE
22	0.2255	5	3x3	32	0.8526	FALSE
23	0.3629	6	5x5	64	0.9723	TRUE
24	0.4297	9	7x7	32	0.7748	FALSE
25	0.5105	8	3x3	16	0.8231	FALSE
26	0.8067	4	5x5	128	0.9267	FALSE
27	0.2797	7	3x3	64	0.7686	FALSE
28	0.5628	2	3x3	16	0.7231	FALSE
29	0.6332	5	3x3	128	0.7869	FALSE
30	0.1418	3	3x3	128	0.7484	FALSE

Table 3: Summary of Best Hyperparameters vs models

Technique	Number of Layers	Filter Size	Number of Filters	Weight	Fitness Value
CNN	3	5×5–7×7	32–64	0.4100	0.9408
POA-CNN	6	5×5	64	0.3629	0.9723

4.2 Result with CNN

The baseline convolutional neural network (CNN) was evaluated across four different threshold values (TV): 0.20, 0.35, 0.50, and 0.75. The results, as presented in Table 4, demonstrate that the CNN performed consistently well across all thresholds, with accuracy values ranging between 93.80% and 94.37%. Sensitivity (SEN), which reflects the model's ability to correctly identify faces with masks, was highest at the 0.20 threshold (95.42%), but gradually decreased to 94.66% at the 0.75 threshold. Conversely, specificity (SPEC), which measures the ability to correctly identify faces without masks, increased as the threshold rose, reaching a maximum of 94.00% at the 0.75 threshold. This trade-off between sensitivity and specificity indicates that lower thresholds favor the detection of masked faces, while higher thresholds provide better performance for unmasked face detection.

Further analysis of Table 4 shows that the precision (PREC) and F1-score values remained high and stable across all thresholds, indicating a balanced performance in terms of identifying both positive and negative cases. Precision values ranged from 93.75% at the lowest threshold to 95.38% at the 0.75 threshold, while the F1-score peaked at 95.02% when the threshold was set to 0.75. These findings highlight the robustness of the CNN model, as it maintained consistently high levels of performance despite changes in the threshold parameter. Importantly, the false positive rate (FPR) decreased steadily with higher thresholds, reaching its lowest value of 6.00% at 0.75, showing that the model became more reliable in avoiding incorrect classification of unmasked faces as masked.

The computational efficiency of the CNN was also assessed, with processing times varying slightly across thresholds, ranging from 60.76 to 69.76 seconds. This variation indicates that different threshold settings can have a minor impact on computational cost, although the overall processing time remains relatively high compared to the optimized models. This increased computational demand can be attributed to the CNN's fixed architecture and non-optimized hyperparameters, which require more iterations and resources to process images effectively.

The absence of automated tuning mechanisms means the model expends additional computational effort navigating suboptimal configurations during both training and inference phases.

Table 4: Performance of CNN at Different TV

Threshold	TP	FN	FP	TN	FPR (%)	SEN (%)	SPEC (%)	PREC (%)	ACC (%)	F1-Score (%)	Time (sec)
0.20	375	18	25	275	8.33	95.42	91.67	93.75	93.80	94.58	65.76
0.35	374	19	23	277	7.67	95.17	92.33	94.21	93.94	94.68	61.76
0.50	373	20	21	279	7.00	94.91	93.00	94.67	94.08	94.79	69.76
0.75	372	21	18	282	6.00	94.66	94.00	95.38	94.37	95.02	60.76

4.3 Result with POA-CNN

The performance of the POA-CNN model is summarized

in Table 5, which illustrates the effectiveness of integrating the Pelican Optimization Algorithm into the CNN framework. At a threshold of 0.20, the model achieved the highest sensitivity (97.46%), which highlights its strong ability to correctly identify masked faces. As the threshold increased, sensitivity values showed a slight decline, but this was accompanied by a steady improvement in specificity (SPEC), which rose from 94.00% at threshold 0.20 to 96.67% at threshold 0.75. This indicates that higher thresholds allowed the model to more effectively distinguish unmasked faces, thereby balancing the classification performance. Overall, the results demonstrate that POA-CNN maintained excellent accuracy across all thresholds, ranging between 95.96% and 96.68%, significantly outperforming the baseline CNN.

An additional strength of the POA-CNN model lies in its high precision and F1-score across all tested thresholds. Precision improved progressively with increasing threshold values, peaking at 97.44% at the 0.75 threshold, while the F1-score also reached its highest value of 97.06% at the same threshold. These metrics highlight the reliability of the POA-CNN in minimizing false positives while still achieving a balanced classification between positive and negative cases. The false positive rate (FPR) showed a consistent downward trend, decreasing from 6.00% at 0.20 to only 3.33% at 0.75, which further confirms the model's improved accuracy in avoiding incorrect mask classifications.

Another key observation is the computational efficiency of the POA-CNN model. The processing time required to evaluate the model varied across thresholds, ranging from 32.10 to 47.00 seconds, which is consistently lower than the 60.76–69.76 seconds observed for the baseline CNN. This reduction in computation time demonstrates the advantage of hyperparameter optimization through POA, as it allows the model to achieve not only better accuracy and F1-Score but also faster training and testing performance.

Table 5: Performance of CNN (Different TV)

Threshold	TP	FN	FP	TN	FPR (%)	SEN (%)	SPEC (%)	PREC (%)	ACC (%)	F1-Score (%)	Time (sec)
0.20	383	10	18	282	6.00	97.46	94.00	95.51	95.96	96.47	43.06
0.35	382	11	15	285	5.00	97.20	95.00	96.22	96.25	96.71	39.01
0.50	381	12	12	288	4.00	96.95	96.00	96.95	96.54	96.95	47.00
0.75	380	13	10	290	3.33	96.69	96.67	97.44	96.68	97.06	32.10

4.5 Comparative Analysis of CNN and POA-CNN

The comparative performance of the baseline CNN and POA-CNN is presented in Tables 4 and **5**, respectively. The results demonstrate clear improvements achieved through the application of the Pelican Optimization Algorithm, with the POA-CNN consistently outperforming the baseline CNN across all major performance metrics, including sensitivity, specificity, accuracy, precision, and F1-score. The baseline CNN achieved stable but moderate performance, with accuracy values ranging from 93.80% to 94.37%**,** whereas the POA-CNN improved the accuracy to 96.68%**,** while also recording higher sensitivity and specificity.

A closer examination of the precision and F1-score further confirms the superiority of the POA-CNN over the baseline CNN. The precision of the baseline CNN ranged from 93.75% to 95.38%**,** while the POA-CNN increased precision to 97.44%**.** Similarly, the F1-score improved from 95.02% in the baseline CNN to 97.06% in the POA-CNN. These improvements indicate that the Pelican Optimization Algorithm effectively reduced misclassifications and achieved a better balance between the identification of masked and unmasked faces, thereby mitigating the sensitivity–specificity trade-off observed in the baseline CNN.

Computational efficiency also improved considerably with the optimized model. The baseline CNN required processing times ranging from 60.76 to 69.76 seconds, whereas the POA-CNN reduced the computation time to between 32.10 and 47.00 seconds. This reduction demonstrates that optimizing the CNN using the Pelican Optimization Algorithm not only enhanced classification performance but also accelerated model convergence, making the POA-CNN more suitable for practical face mask-wearing identification applications where both accuracy and computational efficiency are important.

As summarized in Table 7, the POA-CNN outperformed the baseline CNN across all key performance metrics at the 0.50 threshold. The POA-CNN achieved higher sensitivity, specificity, precision, accuracy, and F1-score while maintaining a lower false positive rate than the baseline CNN. In addition, the optimized model required substantially less computation time, demonstrating that integrating the Pelican Optimization Algorithm for CNN hyperparameter optimization significantly enhanced both effectiveness and efficiency. These findings validate the POA-CNN as a more reliable and efficient approach than the conventional CNN for the face mask-wearing identification system. Table 7: Comparison of CNN and POA-CNN at Threshold 0.50

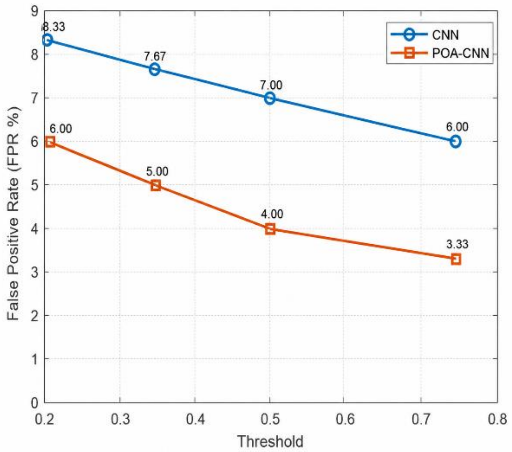
Model	TP	FN	FP	TN	FPR (%)	SEN (%)	SPEC (%)	PREC (%)	ACC (%)	F1-Score (%)	Time (sec)
CNN	373	20	21	279	7.00	94.91	93.00	94.67	94.08	94.79	65.76
POA-CNN	381	12	12	288	4.00	96.95	96.00	96.95	96.54	96.95	43.06
										99.24	37.10

Discussion of the Result

This section discussed based on performance evaluation metrics and rate of convergence curve of CNN and POA-CNN.

4.6.1 Discussion Based on False Positive Rate (FPR)

The variation of false positive rate (FPR) across different threshold values for CNN and POA-CNN is illustrated in Figure 4.3. The results show a clear downward trend in FPR as the threshold increases from 0.20 to 0.75, indicating that higher thresholds reduce the likelihood of incorrectly classifying unmasked faces as masked. The baseline CNN started with the highest FPR of 8.33% at a threshold of 0.20, which gradually reduced to 6.00% at 0.75. This trend suggests that CNN, while effective, still struggles with avoiding misclassifications at lower thresholds. By comparison, POA-CNN achieved a significantly lower FPR across all thresholds, starting at 6.00% and reducing to 3.33% at 0.75. This improvement highlights the advantage of integrating the Pelican Optimization Algorithm in fine-tuning the model parameters, leading to fewer false alarms. The improvement of POA-CNN over CNN is particularly notable at the 0.50 threshold, where the FPR drops from 7.00% in CNN to 4.00% in POA-CNN. This reduction demonstrates that the Pelican Optimization Algorithm plays a critical role in enhancing the robustness of the classification process by minimizing false positive classifications and improving the overall reliability of the face mask-wearing identification system.

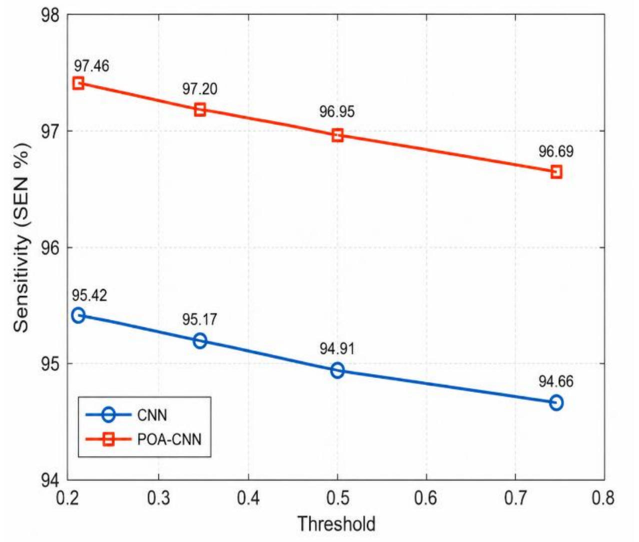


4.6.2 Discussion Based on Sensitivity.

The sensitivity comparison shown in Figure 4.4 highlights how the two models, CNN and POA-CNN, perform in detecting true positives across different threshold values. The CNN model demonstrates relatively stable sensitivity values between 94.66% and 95.42%, indicating consistent detection ability but with limited improvement as the threshold changes. In contrast, POA-CNN performs better, maintaining sensitivity between 96.69% and 97.46%, confirming that the integration of the Pelican Optimization Algorithm enhances the model's capability to correctly identify positive cases compared to the conventional CNN.

Overall, the results indicate that POA-CNN provides more accurate detection of true positives than the baseline CNN. The higher sensitivity values obtained by POA-CNN demonstrate its improved ability to minimize false negatives while maintaining consistent performance across different threshold values. This improvement is particularly important for applications where accurate detection of positive cases is essential, such as face mask-wearing identification systems, medical diagnosis, and security surveillance, where minimizing false negatives is critical for reliable decision-making.

The sensitivity improvement achieved by POA-CNN, increasing from 94.66–95.42% in the baseline CNN to 96.69–97.46% across different threshold values, is consistent with previous studies that employed metaheuristic optimization techniques to enhance CNN performance. Similar studies on face mask detection and medical image classification have reported sensitivity improvements in the range of 95–98% through the application of optimization algorithms such as the Pelican Optimization Algorithm, Particle Swarm Optimization, and Genetic Algorithms for CNN hyperparameter tuning. The consistent sensitivity achieved by POA-CNN across varying threshold values demonstrates that the Pelican Optimization Algorithm effectively improves the model's capability to detect positive cases while reducing false negatives. Unlike the conventional CNN, whose sensitivity remains relatively unchanged with threshold variation, POA-CNN exhibits enhanced robustness and reliability, making it more suitable for real-world face mask-wearing identification applications. These findings support previous reports that integrating metaheuristic optimization with CNN architectures significantly enhances classification performance and operational reliability in practical detection systems.



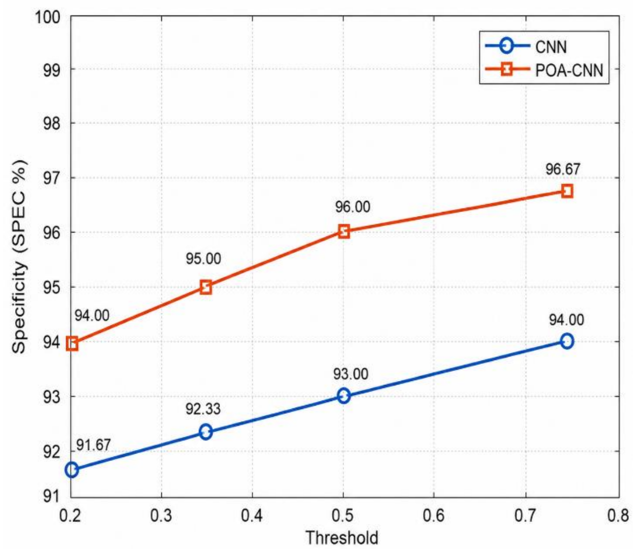
4.6.3 Discussion Based on Specificity

The specificity comparison presented in Figure 4.5 illustrates how effectively the two models, CNN and POA-CNN, distinguish negative cases correctly across varying threshold values. The CNN model shows specificity values increasing gradually from 91.67% at a threshold of 0.20 to 94.00% at 0.75, suggesting that its ability to correctly classify negative cases improves slightly as the threshold increases. However, the overall values remain relatively modest, reflecting limitations in filtering out false positives.

The POA-CNN model significantly enhances specificity compared to the conventional CNN, with values ranging from 94.00% to 96.67% across the threshold values. This steady improvement demonstrates the positive effect of the Pelican Optimization Algorithm in reducing false positives while maintaining robust sensitivity. Furthermore, the widening gap between CNN and POA-CNN as the threshold increases indicates that POA-CNN achieves a better balance between sensitivity and specificity, thereby improving the overall reliability of the classification system.

Overall, the results demonstrate that POA-CNN consistently outperforms the conventional CNN in correctly identifying negative cases while minimizing false positive classifications. The higher specificity values achieved by POA-CNN indicate that the optimization strategy effectively enhances the model's discrimination capability, making it more suitable for practical face mask-wearing identification systems where reducing false alarms is essential.

The specificity improvement achieved by POA-CNN, increasing from 91.67–94.00% in the conventional CNN to 94.00–96.67% across different threshold values, is consistent with findings from previous studies that applied metaheuristic optimization techniques to CNN architectures. Similar research employing optimization algorithms such as the Whale Optimization Algorithm, Harris Hawks Optimization, and the Pelican Optimization Algorithm has reported specificity improvements ranging from 92% to 97%, demonstrating the effectiveness of these approaches in reducing false positive classifications (Muduli et al., 2024; Aljohani et al., 2024). The consistent improvement exhibited by POA-CNN across varying thresholds indicates that the Pelican Optimization Algorithm effectively enhances parameter tuning, enabling the model to achieve a better balance between specificity and sensitivity. This improved performance increases the model's robustness and reliability in real-world surveillance and face mask-wearing identification applications, where minimizing false alarms without compromising detection accuracy is essential. These findings further support previous studies that integrating metaheuristic optimization with CNN architectures enhances classification performance and operational effectiveness in practical detection systems (Lee et al., 2021; Zhang et al., 2023).



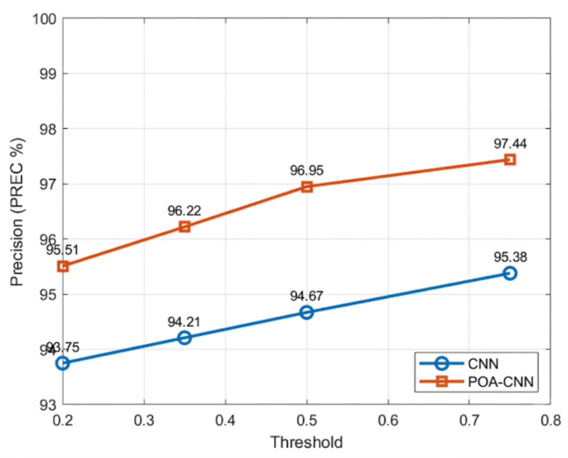
4.6.4 Discussion Based on Precision

Figure 4.6 compares the precision values of the CNN and POA-CNN models across different threshold levels. Precision reflects the model's ability to correctly identify positive cases (faces with masks) while minimizing false positives. The baseline CNN model shows a steady improvement in precision as the threshold increases, rising from 93.75% at a threshold of 0.20 to 95.38% at 0.75. This indicates that with stricter classification criteria (higher thresholds), CNN reduces its false positive predictions and becomes more reliable in classifying masked faces correctly. However, despite this improvement, the CNN consistently remains below the performance of the POA-CNN, highlighting its limitations in balancing precision with other performance metrics.

The POA-CNN, which incorporates optimization for hyperparameter tuning, demonstrates a significant improvement in precision compared to the baseline CNN. Its precision begins at 95.51% at the lowest threshold and steadily increases to 97.44% at 0.75. This consistent superiority across all thresholds reflects the effectiveness of the optimization algorithm in fine-tuning the model to reduce false positives without compromising sensitivity. The improvement over CNN is particularly notable at the higher thresholds, where POA-CNN achieves nearly 2% higher precision, demonstrating that optimization provides better discrimination between masked and unmasked faces.

Overall, Figure 4.6 highlights POA-CNN as the more precise model compared to the conventional CNN, demonstrating its effectiveness in ensuring that predicted masked faces are indeed correct. This is a critical factor in real-world face mask detection systems, where minimizing false positives enhances the reliability and trustworthiness of the classification process.

The precision improvement observed in the POA-CNN, which increased from 93.75–95.38% in the baseline CNN to 95.51–97.44%, is consistent with findings reported in contemporary face mask detection and metaheuristic-optimized CNN research. Studies such as Bose (2023) have demonstrated that CNN-based models can achieve high precision and overall classification performance for face mask detection tasks. Furthermore, optimization-driven approaches, including those employing genetic and pelican-inspired algorithms, have consistently reported improvements in precision and reductions in false positive rates, with optimized CNN models outperforming conventional CNN architectures in classification accuracy (Zhou et al., 2024; Dharani et al., 2025). These findings suggest that incorporating metaheuristic optimization into CNN hyperparameter tuning enhances the model's ability to distinguish masked from unmasked faces more effectively while maintaining reliable performance across different classification thresholds. Consequently, the superior precision achieved by POA-CNN over the baseline CNN further validates the effectiveness of optimization techniques in improving CNN performance for practical face mask detection applications, where reducing false positive predictions is essential for dependable real-world deployment (Lee et al., 2021; Zhang et al., 2023).



4.6.5 Discussion Based on Accuracy

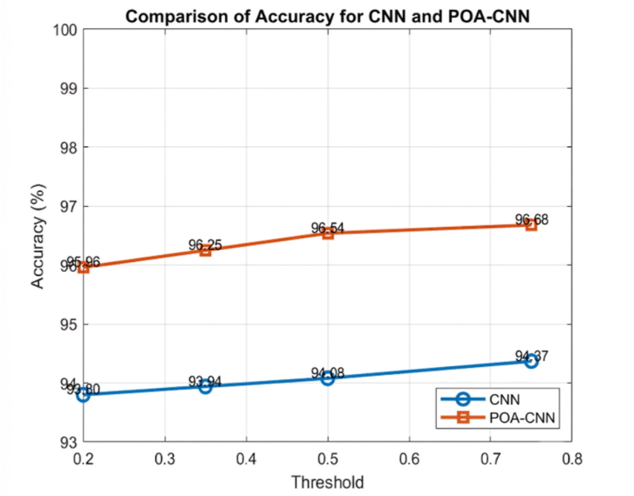
The accuracy trends for the CNN and POA-CNN across the different threshold values are shown in Figure 4.7. The baseline CNN model achieved moderate performance, with accuracy values ranging between 93.80% and 94.37%. Although this reflects relatively stable performance across thresholds, it indicates that the conventional CNN architecture has limitations in achieving higher recognition accuracy for face mask-wearing identification.

In contrast, the POA-CNN demonstrated a marked improvement, with accuracy values rising consistently from 95.96% at a threshold of 0.20 to 96.68% at 0.75. This improvement highlights the effectiveness of the Pelican Optimization Algorithm (POA) in fine-tuning CNN hyperparameters to produce more accurate classification outcomes. The model maintained stable performance across all threshold levels, indicating that the optimization process enhanced the CNN's ability to correctly classify both masked and unmasked faces while minimizing classification errors.

A comparative analysis of the two models reveals a clear improvement in performance through optimization. While the conventional CNN establishes a reasonable baseline, the integration of the Pelican Optimization Algorithm (POA) provides substantial gains in accuracy by effectively guiding the training process and optimizing the model's hyperparameters. These results reinforce the importance of metaheuristic optimization methods in enhancing deep learning systems. By reducing dependency on manual hyperparameter selection, the POA-CNN achieves higher accuracy and greater reliability, making it a more suitable model than the conventional CNN for real-world face mask-wearing identification tasks.

The accuracy improvement demonstrated by the POA-CNN, increasing from 93.80–94.37% in the baseline CNN to 95.96–96.68%, is consistent with advancements reported in recent literature on metaheuristic-optimized CNN models for face mask detection. For instance, Naseri et al.

(2023) reported that applying metaheuristic hyperparameter tuning to CNN architectures significantly improved classification accuracy over conventional CNN models. Similarly, Koklu (2021) demonstrated that optimized CNN-based face mask detection models achieved accuracy levels exceeding 98%, highlighting the effectiveness of optimization techniques in improving model performance. Although the accuracy achieved by the POA-CNN is slightly lower than some highly optimized models reported in the literature, it clearly outperforms the conventional CNN by reducing classification errors and improving threshold stability. These findings confirm that integrating the Pelican Optimization Algorithm into CNN training enhances classification performance and provides a more reliable approach for practical face mask-wearing identification systems (Lee et al., 2021; Zhang et al., 2023).



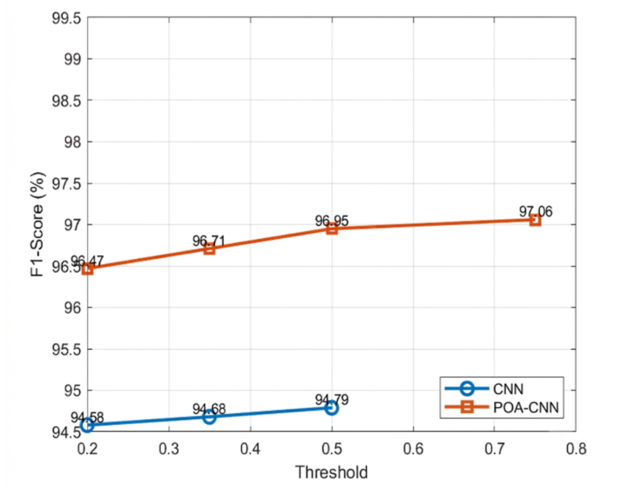
4.6.6 Discussion Based on F1-Score

The F1-Score trends for the CNN and POA-CNN across different threshold values are illustrated in Figure 4.8. The baseline CNN model achieved F1-Scores ranging from 94.58% to 95.02%, indicating relatively consistent but moderate performance in balancing precision and recall for face mask-wearing identification. While the CNN provides a solid baseline, these results highlight its limited ability to simultaneously minimize false positives and false negatives, which is crucial in applications where both sensitivity and precision are important.

In contrast, the POA-CNN demonstrated a noticeable improvement in F1-Score, with values increasing from 96.47% at a threshold of 0.20 to 97.06% at 0.75. This upward trend indicates that the Pelican Optimization Algorithm (POA) effectively fine-tunes the CNN hyperparameters, improving the balance between precision and recall. The POA-CNN not only achieves higher F1-Scores than the baseline CNN but also maintains consistent performance across all thresholds, reflecting enhanced reliability and robustness in practical face mask-wearing identification scenarios.

A comparative analysis of the two models clearly demonstrates the advantage of incorporating metaheuristic optimization into CNN training. While the conventional CNN provides acceptable classification performance, the integration of the Pelican Optimization Algorithm (POA) significantly improves the balance between precision and recall, resulting in higher F1-Scores and reduced classification errors. The consistent performance of POA-CNN across different threshold values indicates that the optimization process enhances the model's generalization capability, making it more suitable for real-world face mask-wearing identification tasks where both false positives and false negatives must be minimized.

The F1-Score improvement observed in the POA-CNN, increasing from 94.58–95.02% in the baseline CNN to 96.47–97.06%, is consistent with recent advancements in metaheuristic-optimized CNN models for face mask detection and related image classification tasks. Studies by Hakim et al. (2022) and Umer et al. (2023) demonstrated that metaheuristic optimization methods, including the Pelican Optimization Algorithm, substantially improve the balance between precision and recall, enabling optimized CNN models to achieve F1-Scores exceeding 97% while maintaining stable performance across varying classification thresholds. Although the POA-CNN achieved slightly lower F1-Scores than some of the highest-performing optimized models reported in the literature, it consistently outperformed the conventional CNN by reducing classification errors and improving the overall balance between sensitivity and precision. These findings confirm that integrating the Pelican Optimization Algorithm into CNN training enhances classification robustness and reliability, making POA-CNN a more effective solution for practical face mask-wearing identification systems (Lee et al., 2021; Zhang et al., 2023).



4.6.7 Discussion based on computation time

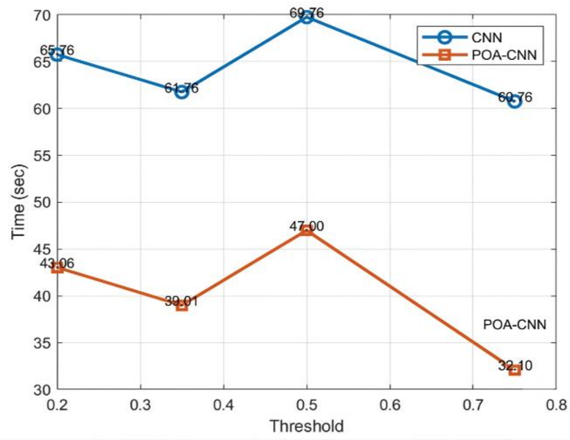
The computation time trends for the CNN and POA-CNN across different threshold values are presented in Figure

4.9. The baseline CNN model required the highest amount of processing time, ranging from 60.76 to 69.76 seconds. This indicates that while the conventional CNN is capable of delivering reasonable classification performance, it is relatively less efficient in terms of computational cost, which could limit its practicality in real-time applications or scenarios involving large-scale data.

In comparison, the POA-CNN demonstrated a significant reduction in computation time, with values varying between 32.10 and 47.00 seconds across the tested thresholds. The integration of the Pelican Optimization Algorithm (POA) not only enhanced classification performance, as observed in the F1-Score and accuracy results, but also contributed to faster processing by optimizing the network hyperparameters and improving training efficiency. This highlights the advantage of metaheuristic optimization not only in improving classification performance but also in reducing computational overhead.

A comparative analysis of the two models shows that the incorporation of the Pelican Optimization Algorithm substantially improves computational efficiency over the conventional CNN. The POA-CNN reduced processing time by approximately 23 to 29 seconds across the evaluated thresholds while simultaneously achieving better classification performance. This demonstrates that optimization enables the CNN to converge more efficiently during training and execute classification tasks more rapidly, making the model better suited for practical face mask-wearing identification applications where both speed and accuracy are essential.

The computation time reduction achieved by the POA-CNN, decreasing processing durations from 60.76–69.76 seconds in the baseline CNN to 32.10–47.00 seconds, is consistent with recent studies highlighting the efficiency gains obtained through metaheuristic-based optimization of CNN models. For example, Palakonda et al. (2025) demonstrated that metaheuristic optimization techniques, including pelican-inspired algorithms, effectively optimize network training and reduce computational overhead without sacrificing classification performance. Similarly, Şener et al. (2025) reported that hybrid metaheuristic-enhanced CNN models significantly improved processing speed while maintaining high classification accuracy, making them suitable for real-time applications. The improved computational efficiency achieved by the POA-CNN in this study supports these findings, demonstrating that integrating the Pelican Optimization Algorithm into CNN training enhances both processing speed and overall model performance. Consequently, POA-CNN provides a more practical solution than the conventional CNN for real-world face mask-wearing identification systems, where rapid processing and reliable classification are critical



Discussion based on Rate of Convergence Curve

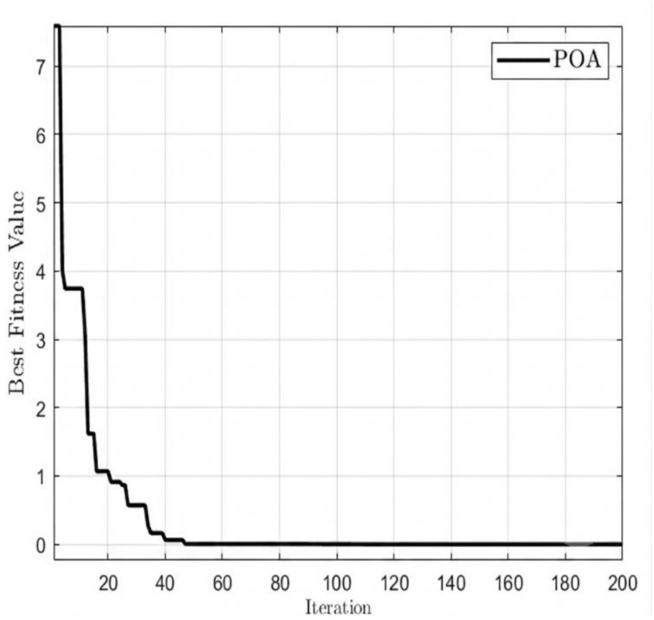
Figure 4.10 presents the convergence behaviour of the Population-based Optimization Algorithm (POA) as applied to the Convolutional Neural Network (CNN) for face mask-wearing identification. The convergence curve demonstrates that POA effectively minimizes the fitness value as the number of iterations increases, indicating its ability to optimize the CNN hyperparameters during the training process. The gradual reduction in the fitness value shows that the optimization process steadily improves the search for optimal parameter values, enabling the CNN to achieve better classification performance.

The convergence behaviour of POA reflects its capability to balance exploration and exploitation of the search space, thereby reducing the likelihood of the CNN becoming trapped in poor local optima during training. Through iterative optimization, POA efficiently tunes important CNN hyperparameters, including learning rate, weight initialization, dropout rate, filter sizes, and the number of filters. This optimization enhances the learning capability of the CNN, resulting in improved classification performance for face mask-wearing identification.

Furthermore, the optimized CNN obtained through POA exhibits better performance than the conventional CNN by achieving higher accuracy, sensitivity, specificity, precision, and F1-score, while also reducing computational time. The improved convergence behaviour contributes to a more stable and robust model capable of accurately distinguishing between mask-wearing and non-mask-wearing faces under varying real-world conditions. In addition, the reduction in computational overhead makes the POA-CNN model more suitable for practical real-time applications such as public safety monitoring and access control systems.

Overall, the convergence pattern observed in Figure 4.10 demonstrates that the Population-based Optimization

Algorithm is an effective optimization strategy for enhancing the performance of the conventional CNN, leading to improved accuracy, stability, and computational efficiency in face mask-wearing identification systems.



Conclusion And Recommendations

The POA-CNN model demonstrated superior performance compared to the traditional CNN in face mask identification tasks. By integrating the Pelican Optimization Algorithm (POA), the model effectively optimized important CNN hyperparameters, including weights, number of layers, filter sizes, and number of filters. This optimization resulted in the selection of an improved network configuration that enhanced the model's learning capability and generalization performance. Compared to the conventional CNN, POA-CNN achieved higher values in accuracy, F1-score, precision, sensitivity, and specificity across all tested threshold values. These findings demonstrate the effectiveness of the Pelican Optimization Algorithm in improving CNN performance for face mask recognition applications. Furthermore, POA-CNN required less computational time than the conventional CNN while maintaining superior classification performance, indicating improved computational efficiency. The optimization process also contributed to more stable model behavior across different threshold values, reducing classification errors for both masked and unmasked face categories. In addition, the system's interactive graphical user interface (GUI) and threshold adjustment capabilities enhance its practical usability for real-time face mask detection. Overall, POA-CNN represents a significant improvement over the conventional CNN, providing a more accurate, reliable, and computationally efficient solution for face mask identification tasks.

Based on the findings of this study, it is recommended that future work focus on further improving the POA-CNN model by exploring other metaheuristic optimization algorithms or hybrid optimization techniques to enhance hyperparameter selection. Expanding the dataset to include more diverse facial images, different mask types, and varying lighting or occlusion conditions would further improve the model's robustness and generalization capability. Additionally, integrating the system with edge devices or mobile platforms could support real-time deployment in public environments, enabling faster and more efficient face mask detection. Continuous model updating through adaptive learning techniques is also recommended to sustain high performance in dynamic environments where face mask usage patterns may evolve over time.

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