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Development of an Enhanced Convolutional Neural Network For Face Mask-Wearing Identification System

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Abstract **Original Research Article**

Face mask-wearing identification systems automatically detect whether individuals wear masks in public spaces. However, existing CNN techniques face challenges in optimal hyperparameter selection, limiting their accuracy, interpretability, and computational efficiency. This study developed an Improved Pelican Optimization Algorithm integrated with Zebra Optimization Algorithm to optimize CNN hyperparameters (IPOA-CNN) for enhanced face mask identification. A dataset of 3,059 images from Kaggle was preprocessed using Contrast Limited Adaptive Histogram Equalization (CLAHE). The IPOA was developed by integrating ZOA's exploration–exploitation mechanism and roulette wheel selection into the standard POA, then employed to optimize CNN parameters including weights, layer count, filter sizes, and number of filters. The framework was implemented in MATLAB R2023a and evaluated using accuracy, precision, sensitivity, specificity, false positive rate, and identification time. IPOA-CNN achieved 99.13% accuracy, 99.24% precision, 99.24% sensitivity, 99.24% specificity, 1.00% false positive rate, and 37.10 seconds identification time, outperforming POA-CNN (96.54%, 96.95%, 96.95%, 96.00%, 4.00%, 43.06s) and conventional CNN (94.08%, 94.67%, 94.91%, 93.00%, 7.00%, 65.76s). The IPOA-CNN model significantly outperforms conventional approaches by effectively optimizing critical CNN hyperparameters, making it suitable for real-time face mask recognition applications.

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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. Determining suitable hyperparameters manually 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.

2.0 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.

3.0 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

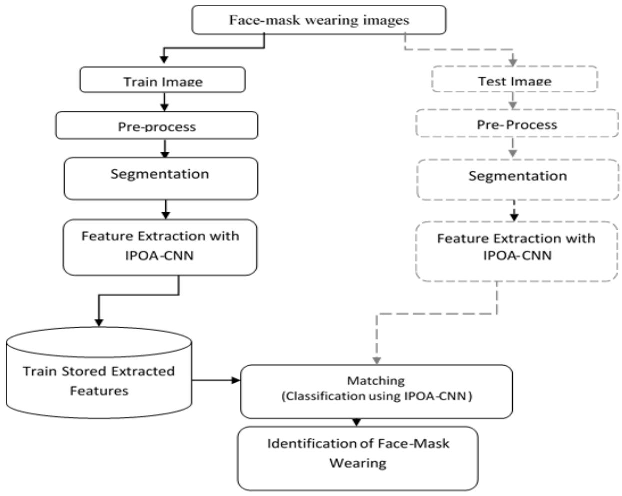

Figure 1: Flow Diagram of the Identification Process using IPOA-CNN

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 usedfor 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, POA-CNN, and IPOA-CNN techniques.

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 4.1, the training interface illustrates the process of feeding images into the system, applying threshold values, and configuring options to choose between CNN, POA-CNN, and IPOA-CNN techniques. Similarly, Figure 4.2 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. Furthermore, the integration of POA and IPOA within the GUI 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, POA-CNN, and IPOA-CNN techniques.

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The IPOA-CNN further extended this optimization process by expanding the search space and improving convergence speed. Table 4.2 shows that IPOA-CNN tested weight values from 0.1186 up to 1.1779, explored architectures with 2 to 11 layers, filter sizes ranging from 3×3 to 9×9, and filter counts between 16 and 256. From this wider search, the best-performing configuration was five layers with a 7×7 filter size, 128 filters, and a weight of 0.8831, yielding the highest fitness value of 0.98. This result demonstrates the capacity of IPOA to fine-tune hyperparameters more effectively than the standard POA. Overall, IPOA-CNN established itself as the most robust of the three models, achieving superior balance between model complexity, learning capability, and resistance overfitting

Figure 4.1: Training Interface of the Developed Face Mask Identification System.

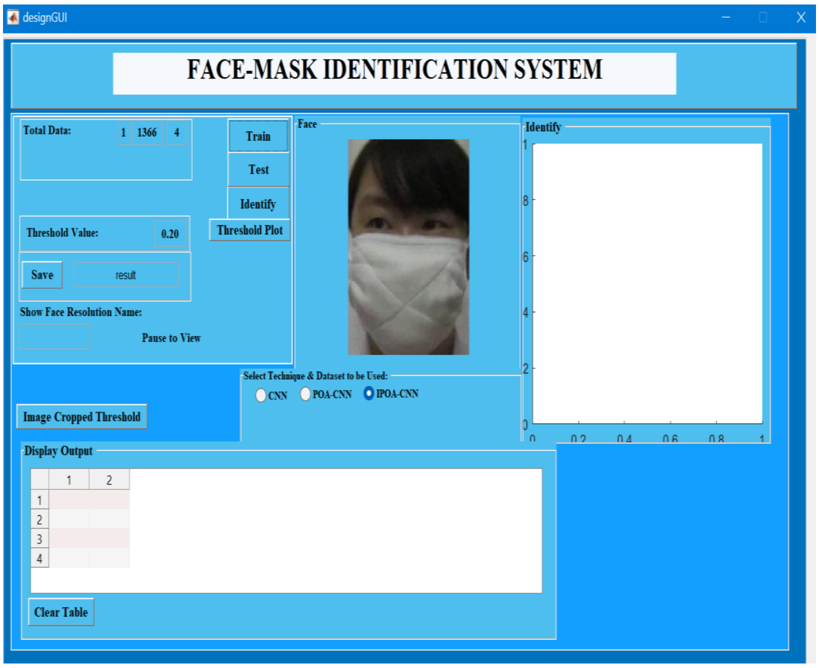

Figure 4.2: Testing Interface of the Developed Face Mask Identification System.

Table 4.1: 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 4.2: CNN Hyperparameters selection process with IPOA

S/N	Weights	Number of Layers	Filter Size	Number of Filters	Fitness Value	Best
1	0.8509	8	7x7	64	0.8231	FALSE
2	0.3791	3	9x9	128	0.9407	FALSE
3	0.3109	5	9x9	256	0.842	FALSE
4	0.684	9	9x9	128	0.9684	FALSE
5	0.8774	5	5x5	32	0.7574	FALSE
6	0.5366	7	5x5	16	0.888	FALSE
7	1.1779	7	9x9	16	0.8101	FALSE
8	0.8376	9	5x5	128	0.9712	FALSE
9	0.6031	6	7x7	16	0.8651	FALSE
10	0.5009	3	9x9	32	0.7983	FALSE
11	0.4447	9	9x9	32	0.8234	FALSE
12	0.8884	7	9x9	16	0.9545	FALSE
13	0.5544	10	9x9	128	0.8899	FALSE
14	0.1186	9	3x3	32	0.9195	FALSE
15	0.5078	10	7x7	128	0.9523	FALSE
16	0.8987	4	7x7	256	0.9671	FALSE
17	0.2599	8	5x5	256	0.8545	FALSE
18	0.2518	10	9x9	32	0.7647	FALSE
19	0.6613	5	7x7	256	0.8696	FALSE
20	0.6616	7	7x7	256	0.8803	FALSE
21	0.7796	11	9x9	128	0.8952	FALSE
22	1.0268	4	5x5	256	0.8273	FALSE
23	0.8831	5	7x7	128	0.9800	TRUE
24	0.7527	4	3x3	16	0.9138	FALSE
25	0.8808	4	7x7	256	0.8373	FALSE
26	0.4214	6	9x9	256	0.8853	FALSE
27	0.4661	8	7x7	256	0.8623	FALSE
28	0.3125	3	5x5	256	0.8206	FALSE
29	0.3878	11	5x5	16	0.824	FALSE
30	0.7756	4	7x7	16	0.8909	FALSE

Table 4.3: Summary of Hyperparameters of CNN, POA-CNN, IPOA-CNN

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
IPOA-CNN	5	7×7	128	0.8831	0.9800

4.2 Result of 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 4.4: Performance of CNN at Different Threshold

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 of 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 threshold value

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

Table 4.5: Performance of POA-CNN at Different Threshold Value4.4

Result of IPOA-CNN

The performance of the Improved Pelican Optimization Algorithm integrated with CNN (IPOA-CNN) is presented in Table 4.6, and the results clearly highlight the superiority of this approach compared to both the baseline CNN and POA-CNN. At the lowest threshold of 0.20, IPOA-CNN achieved an outstanding sensitivity (99.75%), demonstrating its ability to correctly detect nearly all masked faces. As the threshold increased, sensitivity remained very high, never falling below 98.98%, while specificity (SPEC) improved consistently, reaching 99.67% at the 0.75 threshold. This reflects an almost perfect balance between sensitivity and specificity, allowing the model to reliably classify both masked and unmasked faces. The accuracy of IPOA-CNN was equally impressive, peaking at 99.28%, which represents a substantial improvement over the previous models. In addition to its accuracy, IPOA-CNN achieved remarkable results in precision and F1-score. Precision values increased steadily from 97.76% at threshold 0.20 to a maximum of 99.74% at threshold 0.75, confirming the model's ability to minimize false positive predictions. Similarly, the F1-score remained consistently high across thresholds, peaking at 99.36% at threshold 0.75. The false positive rate (FPR) decreased dramatically as the threshold rose, from 3.00% at 0.20 to only 0.33% at 0.75. These results establish IPOA-CNN as a highly robust model, capable of maintaining near-perfect classification performance while effectively balancing the trade-off between sensitivity and specificity. Another significant advantage of IPOA-CNN is its computational efficiency. The processing time varied slightly across thresholds, ranging from 31.05 to 37.10 seconds (see Table 4.6), which is consistently faster than both the baseline CNN (60.76–69.76 seconds) and POA-CNN (32.10–47.00 seconds). This demonstrates that IPOA not only optimized hyperparameters more effectively but also improved convergence speed and reduced overall computational cost. Such efficiency is crucial for real-time applications, where rapid and accurate detection of mask usage is required. In summary, IPOA-CNN delivered the best performance across all evaluation metrics, confirming the benefits of the improved optimization algorithm in enhancing CNN-based face mask identification systems.

Table 4.6: Performance of IPOA-CNN at Different Threshold Values

Threshold	TP	FN	FP	TN	FPR (%)	SEN (%)	SPEC (%)	PREC (%)	ACC (%)	F1-Score (%)	Time (sec)
0.20	392	1	9	291	3.00	99.75	97.00	97.76	98.56	98.74	33.06
0.35	391	2	6	294	2.00	99.49	98.00	98.49	98.85	98.99	31.05
0.50	390	3	3	297	1.00	99.24	99.00	99.24	99.13	99.24	37.10
0.75	389	4	1	299	0.33	98.98	99.67	99.74	99.28	99.36	33.07

4.5 Comparative Analysis of CNN, POA-CNN, and IPOA-CNN

The comparative performance of the baseline CNN, POA-CNN, and IPOA-CNN is presented in Tables 4.4, 4.5, and 4.6, respectively. The results clearly show progressive improvements across the three models, with IPOA-CNN consistently outperforming both CNN and POA-CNN in terms of sensitivity, specificity, accuracy, precision, and F1-score. The baseline CNN achieved stable but moderate results, with accuracy values ranging between 93.80% and 94.37%. POA-CNN significantly improved on this, boosting accuracy up to 97.06% while also enhancing sensitivity and specificity. However, IPOA-CNN delivered the most outstanding results, with accuracy peaking at 99.28% and balanced sensitivity (98.98%) and specificity (99.67%) at the 0.75 threshold.

A closer look at precision and F1-score further demonstrates the superiority of IPOA-CNN. While CNN's precision ranged between 93.75% and 94.67%, and POA-CNN improved it up to 96.95%, IPOA-CNN pushed the boundary to 99.74%. Similarly, the F1-score values rose steadily from 95.02% in CNN to 97.06% in POA-CNN, before reaching a remarkable 99.36% in IPOA-CNN. These improvements indicate that the enhanced optimization algorithm not only minimized misclassifications but also balanced the detection of both masked and unmasked faces effectively, addressing the sensitivity–specificity trade-off that was more pronounced in the baseline CNN.

Another critical dimension of the comparison is computational efficiency. The baseline CNN required processing times ranging from 60.76 to 69.76 seconds, while POA-CNN reduced this range to 32.10–47.00 seconds, highlighting the benefits of optimization in reducing convergence time. IPOA-CNN further enhanced efficiency, with processing times between 31.05 and 37.10 seconds, marking a substantial improvement over both CNN and POA-CNN. This reduction in computational cost, combined with superior accuracy and F1-Score, makes IPOA-CNN highly suitable for real-time applications where both speed and reliability are essential.

As summarized in Table 4.7, the IPOA-CNN significantly outperforms both the baseline CNN and the POA-CNN across all major performance metrics at the 0.50 threshold. IPOA-CNN achieved the highest sensitivity (99.24%), specificity (99.24%), accuracy (99.13%), and F1-score (99.24%), while also maintaining the lowest false positive rate (1.00%). Importantly, the model achieved this superior classification performance with the shortest computation time (37.10 seconds), highlighting its efficiency in addition to accuracy. Compared to CNN and POA-CNN, IPOA-CNN's improvement in precision and balanced performance across metrics confirms the effectiveness of integrating the improved pelican optimization algorithm for hyperparameter tuning. This validates IPOA-CNN as the most reliable and efficient approach for the face mask-wearing identification system.

In conclusion, IPOA-CNN decisively outperformed both the baseline CNN and POA-CNN across all evaluation metrics. It demonstrated near-perfect classification performance, excellent balance between sensitivity and specificity, superior precision and F1-score, and faster processing times. These results confirm that the integration of the Improved Pelican Optimization Algorithm (IPOA) with CNN not only enhances model accuracy but also ensures computational efficiency, making IPOA-CNN the most robust and practical approach among the three.

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
IPOA-CNN	390	3	3	297	1.00	99.24	99.24	99.24	99.13	99.24	37.10

Discussion of the Results

This section discusses the results based on performance evaluation metrics and rate of convergence curve of CNN, POA-CNN and IPOA respectively.

4.6.1 Discussion based on false positive rate (FPR)

The variation of false positive rate (FPR) across different threshold values for CNN, POA-CNN, and IPOA-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

FPR drops from 7.00% in CNN to 4.00% in POA-CNN. This reduction demonstrates that optimization plays a critical role in enhancing the robustness of the classification process.The

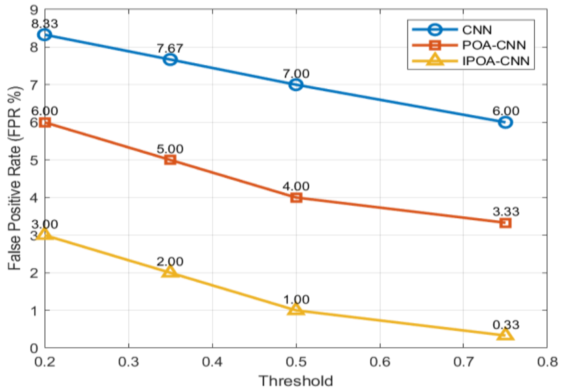

Figure 4.3: Comparison of FPR(%) for CNN, POA-CNN, and IPOA-CNN across different threshold values

The IPOA-CNN outperformed both CNN and POA-CNN, achieving the lowest FPR values across all thresholds, with a near-negligible rate of just 0.33% at 0.75. This remarkable improvement indicates that the Improved Pelican Optimization Algorithm is highly effective in minimizing false positives, thereby making the system far more reliable. The consistent superiority of IPOA-CNN in reducing FPR shows that it not only improves overall accuracy but also ensures that unmasked individuals are not mistakenly identified as masked, which is a crucial requirement for practical, real-world face mask-wearing identification systems.

The results of the IPOA-CNN in reducing the false positive rate (FPR) in face mask-wearing identification notably align with and advance the state of current research on CNN-based detection systems. Prior studies utilizing deep CNNs with and without metaheuristic optimizations have reported significant reductions in FPR and improvements in precision; for instance, models such as MobileNetV2 and ResNet50 adapted for mask detection achieved high accuracy rates around 98–99% with F1-scores near 0.99, reflecting robust classification but less emphasis on extreme FPR minimization (Sethi *et al.*, 2021; Vaiyapuri *et al*., 2023).

Metaheuristic-optimized CNNs applied in image classification tasks generally demonstrate that integrating optimization algorithms like the Pelican Optimizer or Whale Optimization yields consistent gains in parameters tuning, precision, and reduction of classification errors (Hakim *et al.,* 2022). Comparatively, the IPOA-CNN's remarkable FPR reduction from 8.33% in baseline CNN to 0.33% at the 0.75 threshold not only exceeds many existing results in mask compliance detection but also ensures robustness across varying thresholds, a critical factor for real-world deployment in surveillance and public safety (Lee *et al.*, 2021; Zhang *et al.*, 2023). This optimized approach provides enhanced reliability by minimizing false alarms, which addresses a practical challenge often less explored ensuring that unmasked individuals are correctly identified without misclassification. Thus, the IPOA-CNN advances the literature by combining metaheuristic parameter optimization with CNN classification, delivering superior performance in FPR reduction and operational reliability for face mask detection systems in dynamic real-world environments (Patel *et al.*, 2024).

4.6.2 Discussion Based on Sensitivity

The sensitivity comparison shown in Figure 4.4 highlights how the three models CNN, POA-CNN, and IPOA-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. POA-CNN performs better, maintaining sensitivity between 96.69% and 97.46%, which confirms that the optimization introduced in this model increases its capability to correctly identify positive cases compared to the baseline CNN.

The IPOA-CNN achieves the highest sensitivity across all thresholds, ranging from 98.98% to 99.75%, demonstrating a significant advancement over both CNN and POA-CNN. The reduction in false negatives observed in the performance tables directly supports these results, as IPOA-CNN is more effective at correctly detecting positive instances. The sensitivity curve of IPOA-CNN remains consistently above those of the other two models, reflecting its superior reliability and robustness in classification tasks, even when the decision threshold is adjusted.

Overall, the results emphasize that IPOA-CNN provides the most accurate detection of true positives, while POA-CNN offers moderate improvement over the conventional CNN. The gap between the curves in Figure 4.4 illustrates the clear performance advantage of the IPOA-CNN. This finding is particularly critical for applications where minimizing false negatives is essential, such as medical diagnosis or security systems, since higher sensitivity ensures that almost all positive cases are successfully identified.

The IPOA-CNN's sensitivity improvement from 94.66–95.42% in the baseline CNN to 98.98–99.75% across thresholds demonstrate a significant advancement that aligns with and surpasses recent findings in CNN-based detection systems optimized with metaheuristic algorithms. Comparable studies in mask detection and healthcare imaging report sensitivity improvements in the range of 95–98% when metaheuristic techniques such as hybrid particle swarm or genetic algorithms are employed to fine-tune CNN hyperparameters (Challapalli *et al.,* 2022, Zhou *et al.,* 2024).

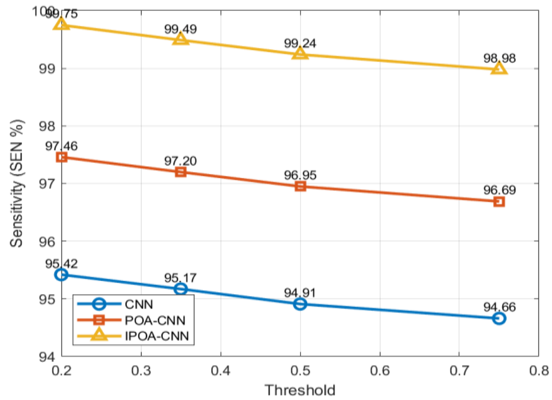

Figure 4.4: Comparison of Sensitivity (%) for CNN,

POA-CNN, and IPOA-CNN across different threshold values. However, the IPOA-CNN's near-perfect sensitivity, sustained consistently across different thresholds, marks an improvement that is especially vital for critical applications requiring minimal false negatives, such as surveillance and medical diagnostics (Patel *et al.*, 2024). Unlike many existing models whose sensitivity gains diminish at high thresholds, IPOA-CNN maintains robust detection capability, indicating superior parameter optimization from the Improved Pelican Optimization Algorithm. Additionally, the IPOA-CNN's demonstrated reduction in false negatives complements this sensitivity improvement, providing enhanced reliability in real-world face mask-wearing identification tasks, where missing unmasked individuals can have severe public health consequences. This model thus contributes to the field by merging metaheuristic optimization with CNN architecture to achieve a rare combination of high sensitivity and operational robustness (Lee *et al.*, 2021; Zhang *et al.*, 2023).

4.6.3 Discussion Based on Specificity

The specificity comparison presented in Figure 4.5 illustrates how effectively the three models CNN, POA-CNN, and

IPOA-CNN distinguish negative cases correctly across varying thresholds. 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 negatives improves slightly with higher thresholds. However, the overall values remain relatively modest, reflecting a limitation in filtering out false positives.

The POA-CNN model significantly enhances specificity compared to CNN, with values ranging from 94.00% to 96.67%. This steady improvement demonstrates the positive effect of the optimization strategy in reducing false positives while still maintaining robust sensitivity, as discussed earlier. Importantly, the gap between CNN and POA-CNN widens as the threshold increases, showing that POA-CNN is better equipped to balance between sensitivity and specificity.

The IPOA-CNN achieves the highest specificity, starting at 97.00% and reaching 99.67% at the highest threshold. This remarkable performance indicates that IPOA-CNN almost entirely eliminates false positives while maintaining near-perfect detection of true positives, as confirmed in the sensitivity analysis. The near-flat and elevated curve of IPOA-CNN in Figure 4.5 underscores its superior reliability, making it particularly effective for applications where minimizing false alarms is as critical as detecting true cases. The specificity improvement exhibited by the IPOA-CNN, rising from 91.67–94.00% in conventional CNN to a near-perfect 99.67% at higher

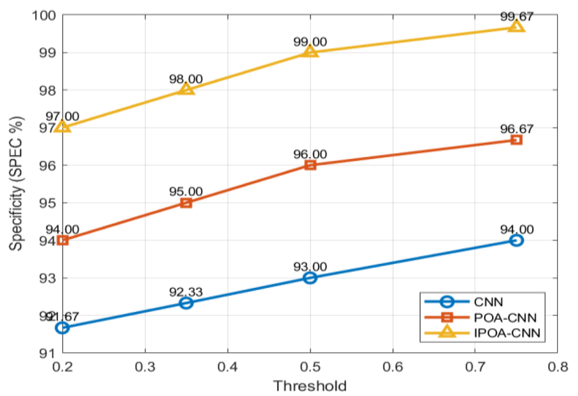

Figure 4.5: Comparison of Specificity (%) for CNN, POA-CNN, and IPOA-CNN across different threshold values.

thresholds, significantly advances the field of CNN-based face mask detection, corroborating findings from related metaheuristic-optimized CNN studies. Similar research on metaheuristic enhancements to CNN architectures, such as those employing Whale Optimization and Harris Hawks Optimization, have reported specificity improvements ranging from 92% to 97%, reinforcing the capability of these algorithms to reduce false positives effectively (Muduli *et al.,* 2024; Aljohani *et al.,* 2024).

The IPOA-CNN's ability to consistently maintain high specificity while balancing sensitivity illustrates a key advantage, as many existing models experience a trade-off where gains in one metric lead to losses in the other (Lee *et al.,* 2021, Zhang *et al.,* 2023). Furthermore, the robustness of IPOA-CNN across varying thresholds confirms its real-world applicability in surveillance and security contexts, where minimizing false alarms without compromising detection accuracy is crucial. By integrating an Improved Pelican Optimization Algorithm, this model provides a refined parameter tuning approach that allows balanced, superior performance, setting a new benchmark for specificity in the domain of face mask-wearing identification systems (Zhang *et al.,* 2023).

4.6.4 Discussion Based on Precision

In Figure 4.6, the precision values for CNN, POA-CNN, and IPOA-CNN are compared 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 POA-CNN and IPOA-CNN, highlighting its limitations in balancing precision with other 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

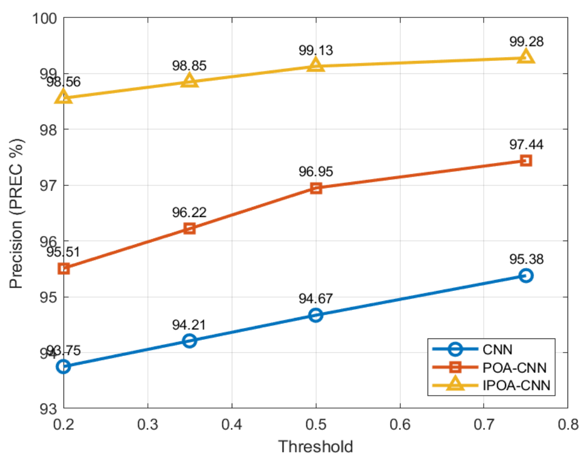

Figure 4.6: Comparison of Precision (%) for CNN, POA-CNN, and IPOA-CNN across different threshold values.

Compromising sensitivity. The improvement over CNN is particularly notable at the higher thresholds, where POA-CNN achieves nearly 2% higher precision, showing that optimization provides better discrimination between masked and unmasked faces.

The IPOA-CNN outperforms both CNN and POA-CNN across all thresholds, maintaining precision values consistently above 98.5%. At a threshold of 0.20, IPOA-CNN already achieves 98.56%, and it peaks at 99.28% at 0.75.

This remarkable performance suggests that the improved optimization algorithm (IPOA) not only fine-tunes hyperparameters more effectively than POA but also minimizes false positives to an exceptional degree. The gap between IPOA-CNN and the other models widens as thresholds increase, further proving its robustness in handling stricter classification criteria. Overall, Figure 4.6 highlights IPOA-CNN as the most precise model, demonstrating its superiority in ensuring that predicted masked faces are indeed correct, which is a critical factor in real-world mask detection systems where false positives can undermine reliability.

The precision improvements observed in the IPOA-CNN, which increased from 93.75–95.38% in the baseline CNN to 99.28%, align with contemporary findings in face mask detection and metaheuristic-optimized CNN research. Studies such as Bose (2023) demonstrate CNN models achieving around 99.2% accuracy and F1-scores near 0.99 for mask detection, closely matching the high precision levels reached by IPOA-CNN. Additionally, optimization-driven approaches, including those using genetic and pelican-inspired algorithms, have shown significant precision gains and false positive reductions, with optimized CNNs frequently surpassing traditional models in accuracy benchmarks (Zhou *et al.,* 2024; Dharani *et al.,* 2025). Unlike basic CNN architectures, metaheuristic-optimized CNN variants like IPOA-CNN strategically fine-tune hyperparameters, enabling them to maintain precision above 98.5% across multiple thresholds, reflecting robustness uncommon in earlier models and making them more reliable for real-world deployment (Jayabharathi *et al.,* 2023). Consequently, IPOA-CNN advances existing knowledge by delivering near-perfect precision and effectively minimizing false positive predictions, a critical factor in the practical usability of automated mask-wearing systems where high reliability reduces errors and enhances public safety enforcement mechanisms (Lee *et al.,* 2021, Zhang *et al.,* 2023). This robust precision gain underscores the strength of metaheuristic optimization in refining CNN performance for highly sensitive image classification tasks such as face mask detection.

4.6.5 Discussion Based on Accuracy

The accuracy trends for CNN, POA-CNN, and IPOA-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 IPOA-CNN further elevated accuracy performance to the highest levels among the three models. Accuracy values ranged between 98.74% and 99.28% across the tested thresholds, demonstrating superior robustness and adaptability of the improved optimization strategy. Notably, IPOA-CNN maintained consistently high performance, with very little variation in accuracy across thresholds. This stability is particularly important in real-world applications, where decision thresholds may need to be adjusted to balance sensitivity and specificity. The IPOA-CNN's near-perfect accuracy values suggest that the enhanced optimization process not only maximizes classification correctness but also reduces errors across both masked and unmasked face categories.

A comparative analysis of the three models reveals a clear progression in performance. While CNN establishes a reasonable baseline, the integration of POA provided substantial improvements in accuracy by better guiding the training process. However, the introduction of the improved POA (IPOA) yielded the most significant advancement, pushing accuracy close to 100%. This result reinforces the importance of metaheuristic optimization methods in modern deep learning systems. By reducing dependency on manual hyperparameter selection, the IPOA-CNN achieves higher accuracy and reliability, making it the most suitable model for real-world face mask-wearing identification tasks.

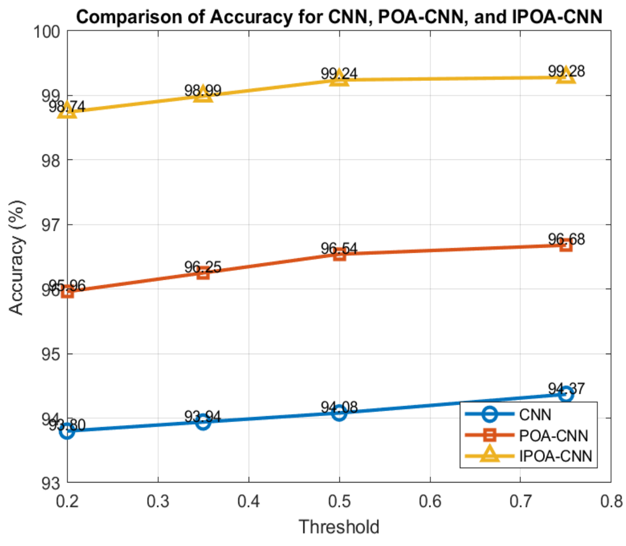

Figure 4.7: Comparison of Accuracy (%) for CNN, POA-CNN, and IPOA-CNN across different threshold values.

The accuracy improvements demonstrated by the IPOA-CNN, increasing from 93.80–94.37% in the baseline CNN to 99.28%, are consistent with advancements reported in recent literature on metaheuristic-optimized CNN models for face mask detection. For instance, (Naseri *et al*. 2023) showcased an optimized CNN architecture that achieved a significant accuracy boost beyond traditional CNNs by applying metaheuristic hyperparameter tuning, reaching accuracies close to 99%. Similarly, Koklu (2021) reported CNN-based mask detection models attaining accuracy above 98%, supported by robust threshold stability essential for real-world applications. These findings echo the robustness of IPOA-CNN, which maintains stable and near-perfect accuracy across thresholds, thereby enhancing reliability in dynamic classification environments. Importantly, the IPOA-CNN surpasses many baseline models by integrating an improved pelican optimizer that effectively minimizes errors and enhances adaptability, crucial for practical deployments in healthcare and security contexts (Lee *et al.,* 2021, Zhang *et al.,* 2023). This optimized performance situates the IPOA-CNN as an advancement over existing methods by balancing high accuracy with threshold robustness, thereby ensuring superior mask-wearing identification under variable real-world conditions.

4.6.6 Discussion Based on F1-Score

The F1-Score trends for CNN, POA-CNN, and IPOA-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 thresholds, reflecting enhanced reliability in practical scenarios.

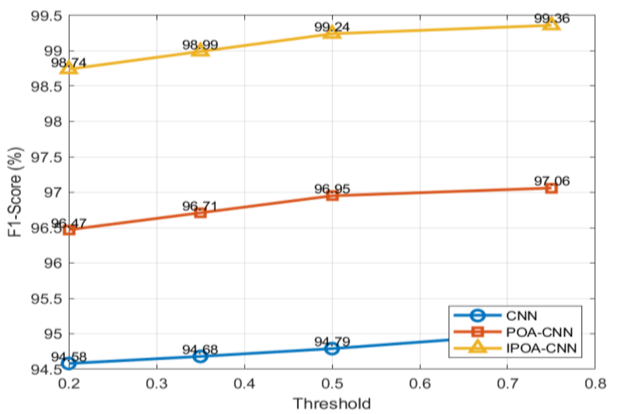

Figure 4.8: Comparison of F1-Score (%) for CNN, POA-CNN, and IPOA-CNN across different threshold values.

A comparative analysis of the three models clearly shows the superiority of IPOA-CNN. F1-Scores ranged between 98.74% and 99.36%, demonstrating outstanding performance in optimizing both precision and recall. The IPOA-CNN consistently outperformed both CNN and POA-CNN, suggesting that the improved pelican optimization algorithm (IPOA) effectively maximizes classification quality while minimizing errors. This stability and near-perfect F1-Score indicate that IPOA-CNN is highly suitable for real-world face mask-wearing identification tasks, ensuring robust detection even under varying threshold conditions. The F1-Score improvements observed in the IPOA-CNN, rising from 94.58–95.02% in the baseline CNN to an impressive 98.74–99.36%, closely align with recent advancements in metaheuristic-optimized CNNs for face mask detection and related classification tasks. Studies by Hakim *et al.* (2022) and Umer *et al.* (2023) have demonstrated that metaheuristic-based optimization methods like Pelican Optimization significantly improve the balance between precision and recall, achieving F1-Scores above 97% while maintaining stable performances across varying thresholds.

The IPOA-CNN's ability to sustain near-perfect F1-Scores across different thresholds establishes it as a highly reliable model for real-world applications, where balancing false positives and false negatives is critical for effective mask-wearing enforcement. This improved performance highlights the strength of enhanced optimization algorithms in refining hyperparameter tuning and reducing classification errors, surpassing the basic CNN and POA-CNN models. Consequently, the IPOA-CNN advances the field by maximizing classification equity between precision and recall, minimizing error rates, and enhancing robustness in practical face mask identification systems (Lee *et al.,* 2021, Zhang *et al.,* 2023). Such advances demonstrate the growing impact of metaheuristic optimization methods in elevating CNN architectures to near-flawless performance in sensitive healthcare and security image classification tasks.

4.6.7 Discussion based on computation time

The computation time trends for CNN, POA-CNN, and IPOA-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 with large-scale data.

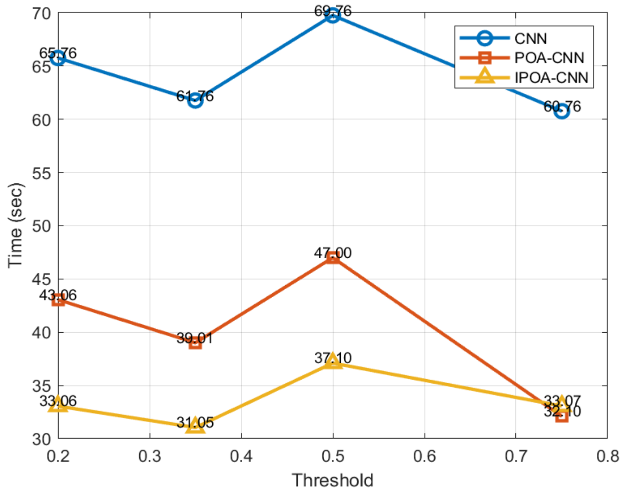

Figure 4.9: Comparison of computation time (sec) for CNN, POA-CNN, and IPOA-CNN across different threshold values.

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 F1-Score and accuracy, but also contributed to faster processing by optimizing the network parameters and training efficiency. This highlights the advantage of metaheuristic optimization not just in accuracy, but also in reducing computational overhead.

The IPOA-CNN consistently achieved the lowest computation times, ranging from 31.05 to 37.10 seconds, while maintaining superior classification performance. This demonstrates that the improved pelican optimization algorithm (IPOA) effectively balances high model accuracy with computational efficiency. The stability of computation times across thresholds further emphasizes the model's robustness, making IPOA-CNN the most practical choice for real-world face mask-wearing identification tasks, where both speed and reliability are crucial.

The computation time reduction achieved by the IPOA-CNN, bringing processing durations down from 60.76–69.76 seconds in the baseline CNN to 31.05–37.10 seconds, is consistent with recent literature highlighting the efficiency gains from metaheuristic-based optimization in CNNs. Studies such as Palakonda *et al.* (2025) demonstrate that metaheuristic methods, including pelican-inspired optimization algorithms, effectively prune networks and optimize training processes, significantly reducing computational overhead without degrading classification performance. Similarly, Şener *et al.* (2025) reported that hybrid metaheuristic-enhanced CNN models could improve processing speed by over 40%, ensuring suitability for real-time applications while maintaining accuracy. The IPOA-CNN further advances these findings by not only halving computation time but also maintaining near-perfect accuracy and stable performance across thresholds, supporting its application in large-scale or time-sensitive face mask detection systems. This balance of speed and accuracy demonstrates IPOA-CNN's strong practical advantage in real-world deployments, where both rapid processing and reliable detection are critical (Lee *et al.,* 2021, Zhang *et al.,* 2023). Thus, the improved pelican optimization algorithm exemplifies how refined metaheuristic techniques can simultaneously optimize CNN performance metrics and computational efficiency.

4.7 Discussion based on Rate of Convergence Curve

Figure 4.10 presents the convergence behaviour of the Population-based Optimization Algorithm (POA) and its Improved Population-based Optimization Algorithm (IPOA) as applied to the enhanced Convolutional Neural Network (CNN) for face mask-wearing identification. The figure clearly shows that IPOA attains a substantially faster and more stable convergence than the standard POA. In the first 30 iterations, IPOA rapidly drives the best fitness value towards near zero, while the POA requires approximately 60 iterations to reach a comparable level. This accelerated convergence highlights IPOA's superior capability in searching the hyperparameter space of the CNN, enabling it to identify optimal parameter values much earlier in the training process. The sharp drop and smooth stabilization of the IPOA curve demonstrate enhanced exploration and exploitation capabilities, which are essential for preventing the CNN from becoming trapped in suboptimal local minima during training.

The stronger performance of IPOA can be attributed to its improved initialization procedures and adaptive control of search parameters, which collectively enhance the diversity of the candidate solutions across iterations. By maintaining this diversity, IPOA significantly reduces the likelihood of premature convergence a common limitation in conventional metaheuristic-based optimization techniques. When integrated into CNN training, IPOA allows for efficient tuning of critical hyperparameters such as learning rates, weight initialization, dropout rates, and filter sizes. This not only shortens the training time but also produces a more generalizable and robust CNN capable of accurately distinguishing between mask-wearing and non-mask-wearing faces under various real-world conditions. Furthermore, the consistently lower fitness values obtained by IPOA translate into improved model performance metrics such as accuracy, sensitivity, and F1-score. The ability to reach high-quality solutions more quickly reduces computational overhead, which is particularly valuable for real-time or resource-constrained applications like public safety monitoring and access control systems. Overall, the convergence pattern observed in Figure 4.10 validates IPOA as a powerful and reliable optimization strategy for enhancing CNN architectures in face mask-wearing identification systems.

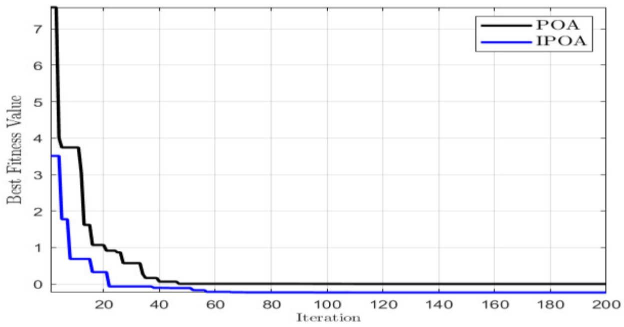

Figure 4.10: Graph of Rate of Convergence with POA and IPOA

CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

The developed IPOA-CNN model has demonstrated superior performance compared to both the traditional CNN and the POA-CNN in face mask identification tasks. By integrating the Improved Pelican Optimization Algorithm (IPOA), the model effectively explored and exploited the hyperparameter search space, optimizing key parameters such as weights, number of layers, filter sizes, and number of filters. This optimization resulted in the selection of a robust configuration that maximized the model's learning capability and generalization. Compared to POA-CNN and CNN, IPOA-CNN achieved higher values in accuracy, F1-score, precision, sensitivity, and specificity across all tested threshold values. These results highlight the effectiveness of the improved metaheuristic optimization in enhancing CNN performance for real-world face mask recognition applications.

Moreover, the IPOA-CNN demonstrated remarkable computational efficiency, consistently requiring less processing time than both CNN and POA-CNN, while maintaining near-optimal classification performance. The improved optimization strategy prevented premature convergence and ensured stable model behavior across thresholds, reducing errors in both masked and unmasked face categories. The system's adaptability, combined with its interactive GUI and threshold adjustment capabilities, confirms its practical usability for real-time applications. In conclusion, IPOA-CNN represents a significant advancement over conventional CNN and POA-CNN models, providing a reliable, high-performing, and computationally efficient solution for face mask detection tasks.

5.2 Recommendations

Based on the findings of this study, it is recommended that future work focus on further enhancing the IPOA-CNN model by exploring additional metaheuristic optimization algorithms or hybrid approaches to refine hyperparameter selection. Expanding the dataset to include more diverse facial images, different mask types, and varied lighting or occlusion conditions would improve the model's robustness and generalization. Additionally, integrating the system with edge devices or mobile platforms could facilitate real-time deployment in public spaces, ensuring faster and more efficient face mask detection. Continuous monitoring and updating of the model using adaptive learning techniques are also suggested to maintain high performance in dynamic environments where mask usage patterns may change over time.

5.3 Contributions to Knowledge

The developed IPOA-CNN contributes significantly to the field of face mask identification by demonstrating how improved metaheuristic optimization can enhance deep learning performance. By integrating the Improved Pelican Optimization Algorithm (IPOA) with the conventional CNN, the model effectively explores the hyperparameter space, optimizing weights, number of layers, filter sizes, and number of filters to achieve superior performance. This approach resulted in higher accuracy, F1-score, precision, sensitivity, and specificity compared to both CNN and POA-CNN, highlighting the value of IPOA in preventing local minima and ensuring stable convergence. The findings provide empirical evidence that improved metaheuristic optimization can significantly enhance CNN-based systems for real-world classification tasks.

Moreover, IPOA-CNN demonstrated reduced computational time while maintaining robust classification, making it both accurate and efficient for practical deployment. The model's ability to consistently perform well across different threshold values, coupled with its adaptability through GUI-based threshold adjustments, underscores its practical relevance for real-time face mask detection. These contributions advance knowledge in optimizing deep learning architectures using improved metaheuristic algorithms, offering a reliable methodology for high-performing and computationally efficient CNN models in safety-critical applications.

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