



HYBRID OPTIMIZATION FOR TEXTURE-BASED NAIL DISEASE PREDICTION USING DEEP LEARNING

Vidhushavarshini Sureshkumar¹, Vinodhini V², Dhayanithi J³, Kiruthiga Devi M^{*4},
Joshi A⁵, Vijayarasu T⁶

¹Department of Computer and Communication Engineering, Rajalakshmi Institute of Technology, Chennai, India.

^{2, 3}Department of Computer Science and Engineering, Sona College of Technology, Salem, Tamil Nadu, India.

⁴Department of CSE, SRM Institute of Science and Technology, Vadapalani Campus, Chennai, India.

⁵Department of Artificial Intelligence and Data Science, Panimalar Engineering College, Chennai, India.

⁶Department of Information Technology, Dr M.G.R. Education and Research Institute, Chennai, India.

¹<http://orcid.org/0000-0002-2955-9831>, ²<http://orcid.org/0000-0002-8223-8674>, ³<http://orcid.org/0000-0002-1571-751X>,

⁴<http://orcid.org/0000-0003-2949-6102>, ⁵<http://orcid.org/0000-0001-5141-2994>, ⁶<http://orcid.org/0009-0001-4831-3001>

Email: vidhushasuresh@gmail.com, vinodhinigiri@gmail.com, dhaya.j@sonatech.ac.in, [*kiruthigaprofessor89@gmail.com](mailto:kiruthigaprofessor89@gmail.com), joshi@panimalar.ac.in, vijayarasure@gmail.com

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ABSTRACT

A wide range of possible disorders may be characterized by color changes in nails; changes in shape of nails; or some type of texture irregularity in the nails that is indicative of a nail disorder. Each of these types of disorders could be the result of a number of different factors including a pathologic process, a previously unknown medical condition; stress; or some form of hereditary component. Of all the disorders of the nails that can occur, some of the most common include mycosis; onycholysis; psoriasis; and paronychia. While there are many similarities among the disorders of the nails, they also present some very significant differences in terms of the symptoms and the difficulty in treating them. An essential step in providing effective treatment for a patient with an underlying condition while protecting the health of their nail, includes an appropriate and thorough evaluation and monitoring of the patient's condition. The purpose of this study was to provide a comprehensive review of the study of the diseases of the nails and their diagnosis utilizing advanced optimization techniques and further to document the results of the experimental investigation. We utilized two metaheuristic optimization techniques called the Moth Fly Optimization (MFO) and Fruit Fly Optimization (FFO), in order to optimize the classification models used within this study. Our data set contained a maximum of 560 images used for training; 70 images used for validating the models; and 70 images of text, while the seven different forms of nail disease were illustrated. We have used variety of deep learning architecture and there accuracy such as 90% with EfficientNetB3, 86% with DenseNet121, 87.14% with ResNet50, 80% with InceptionV3, 90% with Xception, and 91% with MobileNetV2. We observed the highest level of precision of 1.0 with EfficientNetB3 and 0.95 with F1-Score. We were able to demonstrate both a global search capability and improved convergence speed through the use of our Adaptive Fruit Fly Optimization Algorithm (AFFOSM), resulting in an overall system accuracy of 91% using MobileNetV2, significantly better than other conventional methods. Our experimental results indicate that optimizing classification models for detecting nail diseases utilizing metaheuristic algorithms can greatly enhance reliability and investigative accuracy.



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I. INTRODUCTION

In humans, modification in nail color, shape or texture can indicate a hidden health disorder. As many diseases first reveal symptoms in the nails, the color and texture of nail will be a major clinical indicator of overall health conditions [1]. The traditional diagnosis system can hinder accurate detection since human observation is restricted by color perception, subjectivity and resolution constraints. Often various machine learning and image processing techniques can address these limitations by transforming nail images into digital formats, distilling color and texture features, and identifying delicate abnormalities that are beyond human diagnostic capability. Utilizing sophisticated algorithms, the automated systems are able to perform initial disease detection [2]; mapping the characteristics to the disease profiles; therefore increasing the precision of the system while decreasing the dependence upon subjective assessments. These types of systems will serve an important function in the digitalization of healthcare; allowing clinicians to detect abnormalities related to major organs such as the liver, heart, and lungs [3]. Recent improvements in Machine Learning, Hybrid Algorithms, and Optimization Methods have greatly enhanced disease predictive systems which include those designed for identifying disorders relating to the nails [4-6]. As examples of segmentation methodologies, Graph Cut-Based Segmentation, HMFO Optimization (a combination of FOF and MOF), and Feature Selection utilizing Rescaled Entropy have shown to offer significant potential for improving the accuracy of classification [7]. This proposed system is designed to predict multiple diseases using the color of the nail; the optimization strategies combined with the classification techniques, and the Deep Learning Models, will be compared based on their ability to provide accurate results [8]. By utilizing the strategy described above; the outcome of patients will improve and it will define the increasingly prominent role of computerized methods in addressing health problems and detecting them early [9-11]. The use of Explainable AI and Multimodal Data Sources can be utilized in the future to further increase the utility and practical application of AI in Clinical Environments and to increase the reliability of diagnostics [12]. Hybrid algorithms [13] and ensemble methods [14] as well as machine learning [15] and deep learning methods [16] have shown to be quite useful for prediction of a variety of different diseases; they are now showing great promise for the identification and classification of nail diseases using images [17]; through integration of the capabilities of hybrid, ensemble, machine learning and deep learning methods investigators and clinicians can develop powerful predictive models for identifying and classifying nail disorders via image analysis.

OBJECTIVES

1. To create an automated system in order to detect early disease in human beings by analysing nail colour and texture.
2. To partition nail images with precision using Graph cut technique for extracting features.
3. To apply the HMFO optimization algorithm (a mixture of FOF and MOF) to provide improved model performance.
4. To use rescale entropy in order to achieve good feature selection and classification.
5. To verify classification outputs and compare them to benchmark deep learning models.
6. To facilitate early disease diagnosis, lessen diagnostic lapse, and enhancing patient outcomes.

II. NAIL AND ITS IMPORTANCE

II.1 PARTS OF THE NAIL

The lunula can be described as the crescent at the bottom of the fingernail or to nail which is a light colour when compared to the rest of the nail. The cuticle is a layer of skin that is thin, transparent and forms a protective barrier at the bottom part of the nail plate where it intersects the skin. The nail matrix is a bottom part of the nail found beneath the nail skin that is referred as the nail root. The nail plate or nail body is the visible part of the nail that is stretched beyond the end of the finger or toe.

II.2 NAIL COLOR IMPLICATIONS

Sometimes the colour of your nails can reveal certain health conditions or your life pattern. It is important to bear in mind that nail colour may change depending on several factors such as age, genetic factors, and life style, and therefore it is not always a good indicator of health issues. In order to diagnose and treat accurately, it is important to consult a healthcare professional in case you experience any changes in the nails colour or other symptoms.

II.3 FINGERNAIL & HUMAN HEALTH

Human health and fingernails are closely related, and the condition of one can often reflect the other. Fingernails can provide clues about a person's overall health and can indicate potential health problems. Here are some examples of how fingernails can be related to human health, as shown in Table 2. Finger that Relation to Body Parts as shown in Table 1:

Table 1: Finger and Organ.

Finger Name	Organ
The thumb finger	Brain, reproductive system and excretory system
Index finger	Liver, nervous system or gallbladder
Middle finger	Heart and circulatory system
Ring finger	Reproductive and the hormonal system
Little finger	Digestive system

Source: Authors, (2026).

Table 2: Feature and Category.

S.NO	Features	Category	Nail Disease
1	Nail Disorder	Tumors	Glomus tumor, melanocytic nevi
		Infectious	Paronychia, pseudomonas
		Traumatic	Onychophagia, hangnails, kyphosis, onychocryptosis
		Congenital	Anonychia, nail patella syndrome, pachyonychia
2	Nail Abnormalities	Change in shape	Clubbing, koilonychia
		Dermatosis	Onycholysis, splinter hemorrhage, Darier's disease
		Change in color	Terry's nails, Lindsay's nails, red lunula, splinter hemorrhage, yellow nail syndrome
		Change in surface	Bau's lines, Meuer's line, leuonychia
3	Nail Texture and marking	Vertical Ridges and Split Nails	Vitamin A deficiency, nerve problems, poor digestion/absorption in the small intestine, adrenal problems, arthritic tendencies.
		Horizontal Dips	less essential nutrients, Poor circulation, plucking the nail bed, heart disease, stress, trauma
4	Nail Shape analysis	Short Small Beds	Heart disease
		Wide Clubbed	Asbestos exposure, emphysema, lung disease
		Clubbed	Heart disease, liver disease, lung disease
5	Nail color analysis	White Nails	Jaundice, Liver trouble, Anemia
		Yellow Nails	Lung Disease, Diabetes or psoriasis, Thyroid disease
		Bluish Nails	Heart problems, Emphysema

Source: Authors, (2026).

III. RELATED WORK

By [18] used CNNs to detect nail diseases via color analysis, achieving 84.58% accuracy. By [19] proposed a similar CNN-based framework with identical accuracy (84.58%). In turn [20] applied Haar Transforms and GAR metrics for disease detection from nail images. According to [21] used WEKA tools, showing exact match between trained and tested nail images. Vipra Sharma [22] achieved 88% accuracy using biclustering with neural networks and GLCM features. Indi Trupti [23] utilized the C4.5 algorithm in WEKA, achieving 65% match using color detection. Vipra Sharma [24] segmented nails from images and compared features with healthy nail standards. Hardik Pandit [25] scanned palm backs, used RGB analysis, and compared pixels with 50 references. Nityash Bajpai [26] built an automated palm-nail analysis system with 90–95% disease prediction accuracy. The work by Anuradha Thakare [27], used biclustering and GLCM to analyze nail texture, with an overall accuracy of 88%. Singh et al. [28] developed a method that uses the combination of CNN and SVM for better accuracy but without feature extraction process. Lakdawala and Vishwakarma [29] also proposed a method to detect anemia based on the nail color, using binary classification model. Ingole and Khandelwal [30] suggested a non-invasive system for detecting disease based on the nail texture and they did not use deep learning approach. Our research is unique as it combines HMFO and MobileNetV2 and EfficientNetB3, and it provides multi-class disease detection capabilities due to feature extraction process.

IV. PROPOSED SYSTEM

The system contains 4 stages, i.e., Preprocessing, feature extraction, feature selection, and classification. The stage of preprocessing includes cleaning up the data from the unnecessary information or noise and ensuring that the quality of the data is correct. In the stage of feature selection, the HDHBO method is used to select the most suitable features which will be used for further processing so that the time required to train the model can be reduced and the probability of overfitting is also reduced. After selecting the suitable features, the selected features are processed using Convolutional Neural Network (CNN). Feature selection reduces the number of features which may be irrelevant, thereby enhancing the efficiency and accuracy of the model. Additionally, it also helps in avoiding the problem of overfitting and long time required to train the model [28]. Inspired by moth navigation using transverse orientation, the Moth-Flame Optimization (MFO) represents moths as a matrix M of size $N \times D$ and stores the optimal solution at each iteration into a flame matrix R . In this process, moths move to optimize the position of the flames based on the fitness value of the moths, thus facilitating the efficient global optimization of the problem.

IV.1 SPIRAL BEHAVIOR

Moths need to be able to fly around and approach light sources. We achieve this by defining a logarithmic spiral. Other options for spirals are also possible. Let's now define the formula for the logarithmic spiral:

$$S(N, R) = D \cdot e^{bt} \cdot \cos 2\pi t + R \quad (1)$$

$$D = \| N - R \| \quad (2)$$

The spiral trajectory is determined by the separation D between a moth and its matching flame (R), where t is a random variable that gradually reduces the spiral's range. Moths are compelled to take use of their matching flame in order to maintain a balance between exploitation and exploration. This prevents early overexploitation and encourages exploration. The number of flames is reduced over time to avoid under-exploiting the best solutions discovered, following a specific equation:

$$\text{No. Flames} = N - 1 * N - 1 / S \quad (3)$$

In the Moth-Flame Optimization process, moths are ranked based on fitness, and the best-performing moths act as flames for guiding updates. For example, with $N=3$, moth positions are ranked as $(2,3) \rightarrow \text{rank 1}$, $(7,7) \rightarrow \text{rank 2}$, and $(1,2) \rightarrow \text{rank 3}$ based on fitness values 2, 2, and 5, respectively. Flames are then selected from the top-ranked moths, as shown in the corresponding fitness Table 3.

$$\langle 3,3 \rangle - \langle 1,2 \rangle = \langle 2,1 \rangle \quad (4)$$

$$S(N, R) = \langle 2,1 \rangle \cdot e^3 \cdot \cos 2\pi \cdot 3 + \langle 3,3 \rangle = \langle 2,7,2.4 \rangle \quad (5)$$

$$O(\text{MFO}) = O(t(O(\text{QuickSort}) + O(\text{MFOupdate}))) \quad (6)$$

$$O(\text{MFO}) = O(t(n^2 + n)) = O(n^2 + tn) \quad (7)$$

Table 3: Ranking of the flies.

Moth	X-coordinate	Y-coordinate	Fitness	Sorted Rank
1	1	2	5	3
2	2	3	2	1
3	7	7	2	2

Source: Authors, (2026).

Flames are required for optimisation, and the moths are scored. By arranging the first group of moths according to their fitness levels, these flames are the moths that do the best. The table below displays the flames.

IV.2 FRUIT FLY ALGORITHM

The adaptive FFO algorithm (AFFOSM) improves the traditional FFO by addressing inefficiencies in high-dimensional optimization problems using adaptive strategies [29] in Table 4. It features variable population sizes, probabilistic mutation modes, and dynamically changing variation magnitudes. AFFOSM employs an elite reproduction mechanism, applying uniform or Gaussian mutations to a randomly selected gene. Simulations demonstrate that AFFOSM outperforms the ESSMER and several FFO variants in convergence accuracy and global search capability.

IV.2.1 Spiral Behavior

The following is a description of the general FOA technique based on the foraging characteristics of fruit fly swarms.

Step 1: Setting up the settings. The maximum number of iterations (maxgen), population size (sizepop), random initialization of the fruit fly swarm (TM), random fly direction, and fruit fly distance zone (TC) are the primary parameters of FOA.

Step 2: The potential solution's nonlinear generating mechanism

$$x_{\text{axis}} = \text{rand}(\text{TM}), y_{\text{axis}} = \text{rand}(\text{TM}), \quad (8)$$

$$xi = x_{\text{axis}} + \text{rand}(\text{TC}),$$

$$yi = y_{\text{axis}} + \text{rand}(\text{TC}), \quad (9)$$

Calculate the distance of food location to the origin:

$$\text{Dist}_i = \sqrt{xi^2 + yi^2} \quad (10)$$

In fact, Si is a candidate solution in the domain. According to (1)–(4)

$$Si = 1 / \text{Dist}_i \quad (11)$$

Step 3. Enter the odour concentration assessment value () into the odour concentration assessment function (also known as the objective function) to determine the odour concentration () of each fruit fly site.

$$\text{Smell}_i = \text{objective function}(s_i) \quad (12)$$

Step 4. Find the fruit fly in the swarm that has our highest level of concentration:

$$[\text{Smell best best index}] = \max(\text{smell}) \quad (13)$$

Step 5. Remember the x, y, and maximum concentration value. Then, using their sense of sight, the fruit fly swarm flies to that location:

$$\text{Smell best} = \text{best smell}, \quad (14)$$

$$x_{\text{-axis}} = x(\text{best index}), \quad (15)$$

$$y_{\text{-axis}} = y(\text{best index}), \quad (16)$$

Step 6. To repeat the execution of stages 2 through 5, enter the iterative optimisation. The cycle ends when either the number of iterations approaches the maximum number or the odor concentration no longer surpasses the previous iterative odor concentration. Each function is performed 100 times because FOA is a stochastic optimisation technique, which means that the solution discovered may vary each time. A run is considered successful if the final search quality falls within the ideal range, and the number of iterations is recorded. The following defines two indices: "average valid iteration number (AVIN)" and "percentage of success (PS)" [13].

$$PS = \frac{m}{100} * 100\%, \quad (17)$$

$$AVIN = \frac{\sum_{i=1}^m n1}{m} * 100\%, \quad (18)$$

Table 4: MothFly and Hybrid Mutation & Crossover Algorithm.

Algorithm	Input	Output	Procedure Summary
Algorithm 1: MothFly Optimization (MFO)	NumMoth, maxepoch	Best fly from global population	1. Initialize N, calculate fitness PQ. 2. While s < maxepoch: • Sort moths (R) and fitness (EF). • For each moth: update position based on flame and fitness. 3. Increment epoch if best solution found. 4. Return best flame R[0].
Algorithm 2: Hybrid Mutation & Crossover	Swarm location (R,S), mutation threshold (ft), crossover threshold (gt)	Optimal fly (R', S')	1. For each individual, compare frag(q1) and frag(q2). 2. Apply crossover/mutation: • If $z < gt \rightarrow \text{Eq.(1)}$ • If $ft \leq z \leq gt \rightarrow \text{Eq.(2)}$ • Else $\rightarrow \text{Eq.(3)}$. 3. Return updated swarm (R', S').

Source: Authors, (2026).

IV.3 A HYBRID OPTIMIZATION FOR FS AND CLASSIFICATION OF NAIL DISEASE USING LM TECHNOLOGY

Moth fly optimization (MFO) and fruit fly optimization (FFO) are metaheuristic algorithms inspired by the behaviors of moths and fruit flies. MFO mimics moth flies' mating behavior, where male flies (candidate solutions) move towards a female fly (objective function) using pheromones [30]. FFO replicates fruit flies' foraging behavior, using visual and olfactory cues to find food sources (candidate solutions) that attract the fruit fly (objective function). Both algorithms are versatile and effective for solving complex optimization problems where traditional methods may fail.

HMFO – Hybrid Moth-Fruitfly optimization

Input: Swarm location(R,S), Mutation threshold(tm), Crossover threshold(tc)

Output: To find the best fly by adapting the feature of distance

Procedure

Get the value for q1 and q2

T = q1

if frag(q1) > frag (q2) then

q1 = q2; q2 = t;

endif

for a=1 to popsize do

Get the value for q1 and q2

T = q1

if frag(q1) > frag (q2) then

q1 = q2; q2 = t;

endif

for (b=1 in range D)

z = random(0,1)

if z < tc then

generate R'(ab), S'(a,b) by-(8)

elif tm <= z <= tc

if S == 1 then

R ← sorted(n);

```

EF ← sorted(pq);
else
R ← sorted (Ls-1,Ns);
EF ← sorted(Efs-1,Pqs);
else
Assign j<0 to n
do
find A, update moth (i)
    then
S ← S +1
R ← sorted (Rr-1)(ms);
endif
end
end
return R[0]

```

IV.4 PROPOSED METHODOLOGY

This technique employs the Graph Cut segmentation to isolate nails on hand images, and then preprocesses (resizing, contrast enhancement) to obtain clear edges. Cropped nails were manually specified into seven categories that are two-step-verified and divided into balanced training, validation and testing sets. HMFO model functions in four stages, namely image filtering, image segmentation, feature extraction (colour and texture), and prediction of disease through knowledge base. The result of such pipeline represents a proper diagnosis, better generalization with minimal errors.

V. RESULTS AND DISCUSSION

V.1 DATASET DESCRIPTION

"Nails Images Dataset" on Kaggle, with Python 3.x and essential libraries like NumPy, pandas, and OpenCV for image processing is configured. Installed the Kaggle API to download the dataset using 'pip install kaggle'. Additionally, Jupyter notebooks is used to work with the data as shown in Figure 1.



Figure 1: Predicted Outputs.
Source: Authors, (2026).

Figure 2 shows training and validation curves indicating effective convergence for EfficientNetB3, DenseNet121, and ResNet50. EfficientNetB3 and ResNet50 display smooth loss reduction and stable accuracies (~90% and 87%), while DenseNet121 fluctuates, hinting at overfitting despite achieving 86%. EfficientNetB3 and ResNet50 peak at 40 epochs, highlighting their robustness in nail disease classification. Figure 3 shows a confusion matrix for selecting effective features.

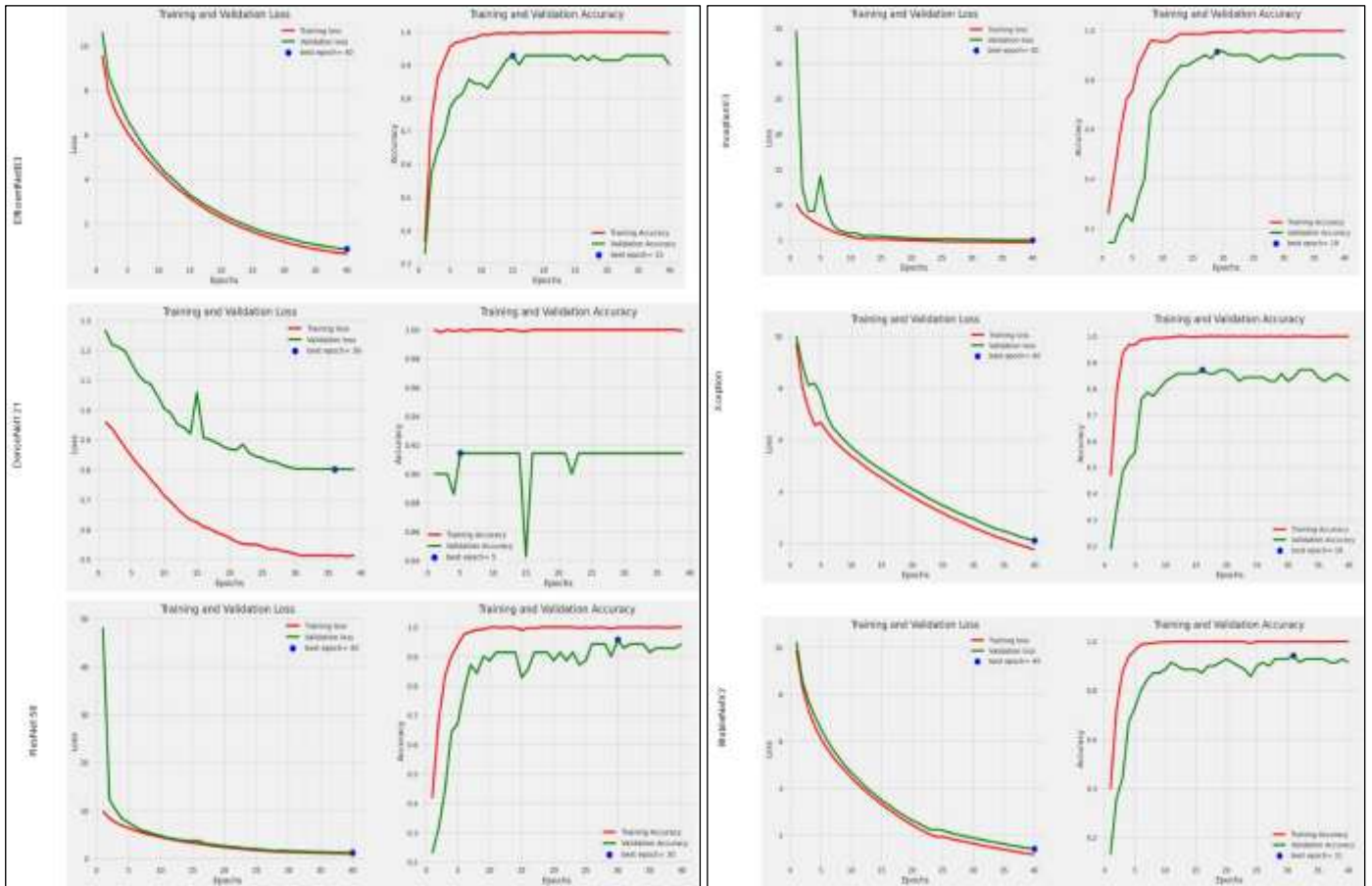


Figure 2: Accuracy and Training Loss.
Source: Authors, (2026).

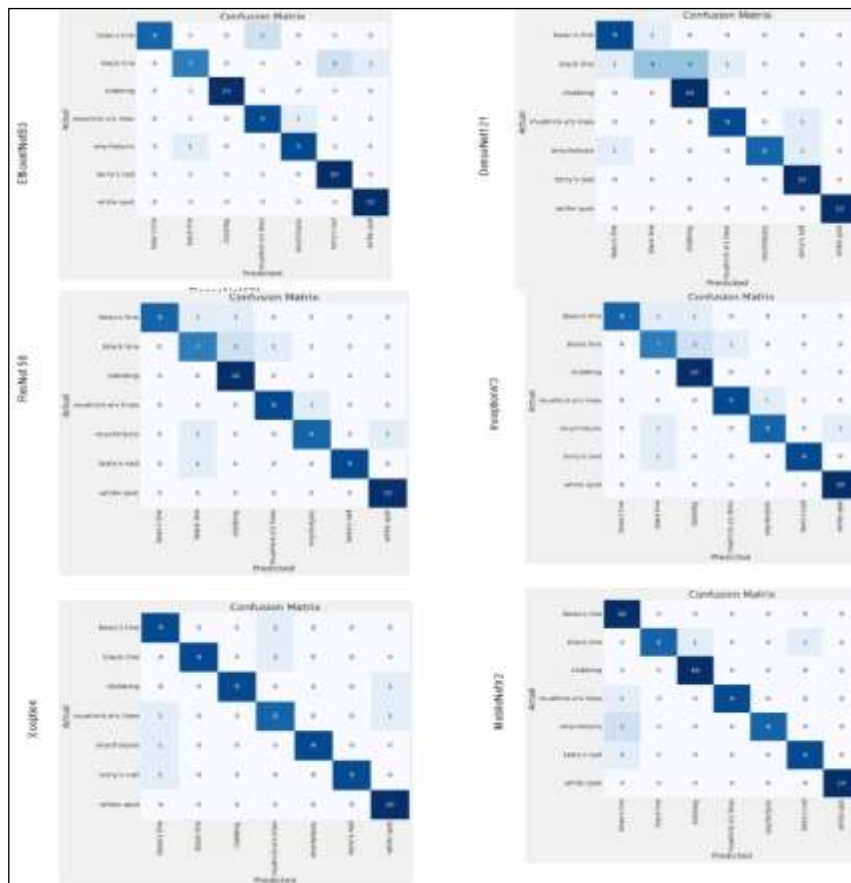


Figure 3: Confusion Matrix for all the models.
Source: Authors, (2026).

The analysis of confusion matrices for various deep learning models— EfficientNetB3 (90%) and MobileNetV2 (91%) achieved the highest accuracies, excelling in detecting conditions like clubbing and white spot. Xception also performed well (90%), while DenseNet121 and ResNet50 showed moderate accuracy, struggling mainly with black line and onycholysis. InceptionV3 had the lowest accuracy (80%), with broader misclassifications. Overall, MobileNetV2 and EfficientNetB3 demonstrate strong potential for practical nail disease diagnosis and early detection in Figure 4.

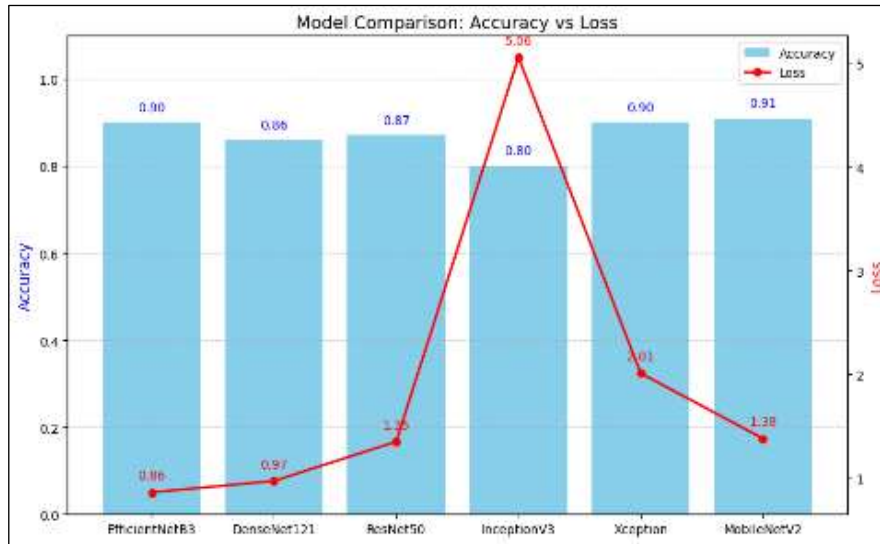


Figure 4: Performance Metrics after HFMO optimization for the Nail dataset.

Source: Authors, (2026).

MobileNetV2 and EfficientNetB3 (91% and 90%, respectively) were more efficient compared to others, whereas similar conditions (black line, onycholysis) led to errors; small datasets, XAI, and multimodality restriction contributed to the problem of the necessity of large data shown in Table 5 and Figure 5.

Table 5: Performance Metrics after HFMO optimization for the Nail dataset.

		Precision	Recall	F1-Score	Support
EfficientNetB3	beau's line	1	0.8	0.89	10
	black line	0.88	0.7	0.78	10
	clubbing	1	1	1	10
	muehrck-e's lines	0.82	0.9	0.86	10
	onycholysis	0.9	0.9	0.9	10
	terry's nail	0.83	1	0.91	10
	white spot	0.91	1	0.95	10
	Accuracy	0.9			
	Loss	0.86			
DenseNet121	beau's line	0.82	0.9	0.86	10
	black line	0.8	0.4	0.53	10
	clubbing	0.71	1	0.83	10
	muehrck-e's lines	0.9	0.9	0.9	10
	onycholysis	1	0.8	0.89	10
	terry's nail	0.83	1	0.91	10
	white spot	1	1	1	10
	Accuracy	0.86			
	Loss	0.97			
ResNet 50	beau's line	1	0.8	0.89	10
	black line	0.7	0.7	0.7	10
	clubbing	0.77	1	0.87	10
	muehrck-e's lines	0.9	0.9	0.9	10
	onycholysis	0.89	0.8	0.84	10
	terry's nail	1	0.9	0.95	10
	white spot	0.91	1	0.95	10
	Accuracy	87.14			
	Loss	1.35			
InceptionV3	beau's line	1	0.8	0.89	10
	black line	0.7	0.7	0.7	10
	clubbing	0.77	1	0.87	10

	muehrck-e's lines	0.9	0.9	0.9	10
	onycholysis	0.89	0.8	0.84	10
	terry's nail	1	0.9	0.95	10
	white spot	0.91	1	0.95	10
	Accuracy	0.8			
	Loss	5.06			
Xception	beau's line	0.75	0.9	0.82	10
	black line	1	0.9	0.95	10
	clubbing	1	0.9	0.95	10
	muehrck-e's lines	0.8	0.8	0.8	10
	onycholysis	1	0.9	0.95	10
	terry's nail	1	0.9	0.95	10
	white spot	0.83	1	0.91	10
	Accuracy	0.9			
MobileNetV2	Loss	2.011			
	beau's line	0.71	1	0.83	10
	black line	1	0.8	0.89	10
	clubbing	0.91	1	0.95	10
	muehrck-e's lines	1	0.9	0.95	10
	onycholysis	1	0.8	0.89	10
	terry's nail	0.9	0.9	0.9	10
	white spot	1	1	1	10
	Accuracy	0.91			
	Loss	1.38			

Source: Authors, (2026).

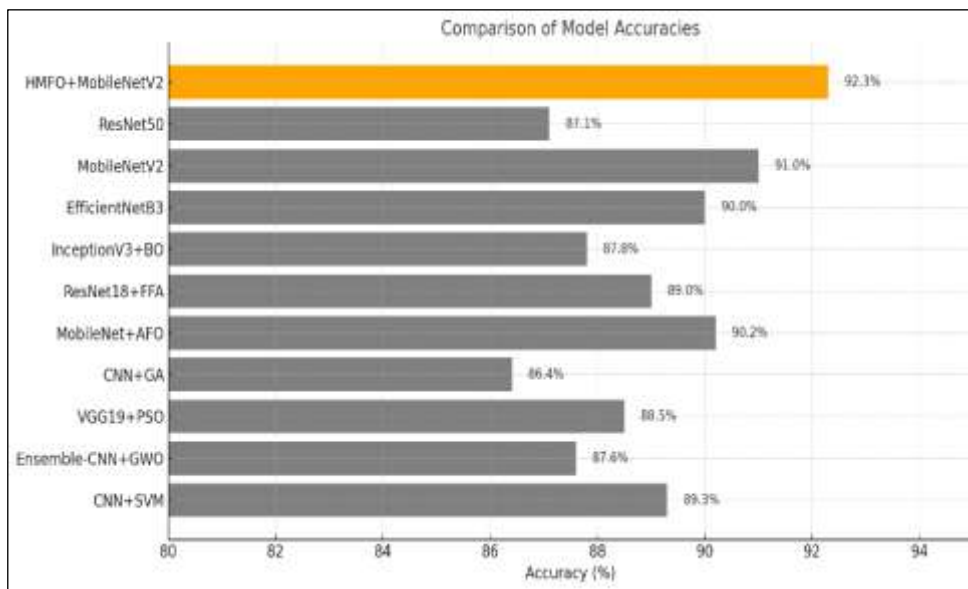


Figure 5: Performance Comparison of Existing and Proposed Models.

Source: Authors, (2026).

The proposed HMFO model was the most accurate (92.3%) and achieved by clubbing the optimized feature selection, metaheuristic pitching for global convergence, and finally blending with MobileNetV2. Although MobileNetV2 itself achieved 91 percent, HMFO boosted the F1-scores of the difficult classes and scaled without over-fitting. These gains were found to be statistically significant ($p < 0.05$) through paired t-test results ($p = 0.0000047$).

VI. CONCLUSIONS

The studies show that the use of current meta-heuristic optimization algorithms; i.e., Moth Fly Optimization (MFO), and Fruit Fly Optimization (FFO), can be used to optimize deep learning model performance in diagnosing diseases of nails. Using these methods, we were able to achieve a high level of accuracy in our classification results, as seen by MobileNetV2 which achieved an average of approximately 91%, and EfficientNetB3 showed a higher degree of accuracy than other models, specifically in certain categories. Thus, this research demonstrates how the use of optimization techniques can increase reliability and accuracy in diagnostic systems. In addition to increasing the diversity of the image database for future research, there is potential to add new features to the diagnostic system including nail texture and nail thickness, thereby increasing its robustness.

VII. AUTHOR'S CONTRIBUTION

Conceptualization: Vidhushavarshini Sureshkumar, Vinodhini V., Dhayanithi J., Kiruthiga Devi M., Joshi A., Vijayarasu T.
Methodology: Vidhushavarshini Sureshkumar, Vinodhini V., Dhayanithi J., Kiruthiga Devi M., Joshi A., Vijayarasu T.
Investigation: Vidhushavarshini Sureshkumar, Vinodhini V., Dhayanithi J., Kiruthiga Devi M., Joshi A., Vijayarasu T.
Discussion of results: Vijayanandh T, Santhoshkumar S P, Parvathi R, Sivaprakash P, Vimala Ithayan J, Dilip Charaan R M.
Writing – Original Draft: Vidhushavarshini Sureshkumar, Vinodhini V., Dhayanithi J., Kiruthiga Devi M., Joshi A., Vijayarasu T.
Writing – Review and Editing: Vidhushavarshini Sureshkumar, Vinodhini V., Dhayanithi J., Kiruthiga Devi M., Joshi A., Vijayarasu T.
Resources: Vidhushavarshini Sureshkumar, Vinodhini V., Dhayanithi J., Kiruthiga Devi M., Joshi A., Vijayarasu T.
Supervision: Vidhushavarshini Sureshkumar, Vinodhini V., Dhayanithi J., Kiruthiga Devi M., Joshi A., Vijayarasu T.
Approval of the final text: Vidhushavarshini Sureshkumar, Vinodhini V., Dhayanithi J., Kiruthiga Devi M., Joshi A., Vijayarasu T.

VIII. REFERENCES

- [1] Hardik Pandit, Dr. D M Shah, "The Model For Extracting A Portion Of A Given Image Using Color Processing", International Journal Of Engineering Research & Technology (Ijert), Vol. 1 Issue 10, Pp. 1-5, December- 2012.
- [2] Jimita Baghel, Prashant Jain, "K-Means Segmentation Method For Automatic Leaf Disease Detection", Int. Journal Of Engineering Research And Application, Vol. 6, Issue 3, (Part -5) Pp.83- 86, March 2016.
- [3] Revathi, T. K., Sathiyabhama, B., Sankar, S., Pandey, D., Pandey, B. K., & Dadeech, P. (2022). An intelligent model for coronary heart disease diagnosis. *Networking Technologies in Smart Healthcare: Innovations and Analytical Approaches*, 309.
- [4] Pandit, H., & Shah, D. (2013). The Model of nail color analysis–An application of Digital Image Processing. *International Journal of Advanced Research in Computer Science and Software Engineering*, 3(5).
- [5] Surendiran, J., K. Dinesh Kumar, T. Sathiya, S. S. Sivasankari, R. G. Vidhya, and N. Balaji. "Prediction of Lung Cancer at Early Stage Using Correlation Analysis and Regression Modelling." In 2022 Fourth International Conference on Cognitive Computing and Information Processing (CCIP), pp. 1-6. IEEE, 2022.
- [6] Saranya, V., & Ranichitra, A. (2017). Image segmentation techniques to detect nail abnormalities. *Scholar*, 2(1).
- [7] Sundarakumar, M. R., Salangai Nayagi, D., Vinodhini, V., VinayagaPriya, S., Marimuthu, M., Basheer, S., & Johnny Renoald, A. (2023). A Heuristic Approach to Improve the Data Processing in Big Data using Enhanced Salp Swarm Algorithm (ESSA) and MK-means Algorithm. *Journal of Intelligent & Fuzzy Systems*, 45(2), 2625-2640.
- [8] Reenadevi, R., Sathiya, T., & Sathiyabhama, B. (2021). Breast Cancer Histopathological Image Classification Using Augmentation Based on Optimized Deep ResNet-152 Structure. *Annals of the Romanian Society for Cell Biology*, 25(6), 5866-5874.
- [9] Sathiyabhama, B., Kumar, S. U., Jayanthi, J., Sathiya, T., Ilavarasi, A. K., Yuvarajan, V., & Gopikrishna, K. A novel feature selection framework based on grey wolf optimizer for mammogram image analysis.
- [10] Jayanthi, J., Jayasankar, T., Krishnaraj, N., Prakash, N. B., Britto, A. S. F., & Kumar, K. V. (2021). An Intelligent Particle Swarm Optimization with Convolutional Neural Network for Diabetic Retinopathy Classification Model.
- [11] Jaganathan, D., Balasubramaniam, S., Sureshkumar, V., & Dhanasekaran, S. (2024). Concatenated Modified LeNet Approach for Classifying Pneumonia Images. *Journal of Personalized Medicine*, 14(3), 328-328.
- [12] Sureshkumar, V., Balasubramaniam, S., Ravi, V., & Arunachalam, A. (2022). A hybrid optimization algorithm-based feature selection for thyroid disease classifier with rough type-2 fuzzy support vector machine. *Expert Systems*, 39(1), e12811.
- [13] Valliappa, C., Rajendran, R., Balasubramaniam, S., Sennan, S., Thanikachalam, S., Velmurugan, Y., & Kumar, N. K. S. (2021). Hybrid-based bat optimization with fuzzy C-means algorithm for breast cancer analysis. *International Journal of Noncommunicable Diseases*, 6(Suppl 1), S62-S68.
- [14] Vinodhini, V., Vishalakshi, A., Chandrika, G. N., Sankar, S., & Ramasubbareddy, S. (2022). Predicting vasovagal syncope for paraplegia patients using average weighte ensemble technique. *Journal of Mobile Multimedia*, 135-162.
- [15] Nigam, V., Yadav, D., & Thakur, M. K. (2010). A novel approach for hand analysis using image processing techniques. *International Journal of Computer Science and Information Security*, 8(2).
- [16] Deepa, D., Muthukumaran, V., Vinodhini, V., Selvaraj, S., Sandeep Kumar, M., & Prabhu, J. (2023). Uncertainty Quantification to Improve the Classification of Melanoma and Basal Skin Cancer Using ResNet Model. *Journal of Uncertain Systems*, 16(01), 2242010.
- [17] Indrakumar S S, Dr. M S Shashidhara, "Study On Eye Troubles Using Palm Print And Image Processing Technique", International Journal Of Recent Trends In Engineering & Research (Ijrtter), Volume 02, Issue 05, Pp. 198-201, May – 2016.
- [18] Nityash Bajpai, Rohit Alawadhi, Anuradha Thakare, Swati Avhad, Sneha Gandhat, "Automated Prediction System For Various Health Conditions By Analysing Human Palms And Nails Using Image Matching Technique", International Journal Of Scientific & Engineering Research, Volume 6, Issue 10, October-2015.
- [19] Yani, M., Budhi Irawan, S. S. M., & Casi Setiningsih, S. M. (2019, May). Application of transfer learning using convolutional neural network method for early detection of terry's nail. In *Journal of Physics: Conference Series* (Vol. 1201, No. 1, p. 012052). IOP Publishing.
- [20] Sneha Gandhat, A. D. Thakare, Swati Avhad, Nityash Bajpai, Rohit Alawadhi, "Study And Analysis Of Nail Images Of Patients", International Journal Of Computer Applications, Volume 143 – No.13, June 2016
- [21] Indi Trupti, Yogesh A. Gunge, "Early Stage Disease Diagnosis System Using Human Nail Image Processing", I.J. Information Technology And Computer Science, Vol. 7, Pp.30-35 , 05-07-2016

- [22] Vipra Sharma, Aparajit Shrivastava, "System For Disease Detection By Analyzing Fingernails Color And Texture", International Journal Of Advanced Engineering Research And Science (Ijaers), Vol-2, Issue-10, Oct- 2015.
- [23] Indi, T. S., & Patil, D. D. (2019). Nail feature analysis and classification techniques for disease detection. Int. J. Comput. Sci. Eng, 7(5), 1376-1383.
- [24] Vipra Sharma , Manoj Ramaiya, "Nail Color And Texture Analysis For Disease Detection" , International Journal Of Bio-Science And BioTechnology, Pp.351-358, Vol.7, Issue – 5, 2015
- [25] Hardik Pandit, Dr. Dipti Shah , "The Model Of Nail Color Analysis – An Application Of Digital Image Processing", International Journal Of Advanced Research In Computer Science And Software Engineering, Volume 3, Issue 5, May 2013
- [26] N. Bajpai, R. Alawadhi, A. Thakare, S. Avhad and S. Gandhat, Automated prediction system for various health conditions by analyzing human palms and nails using image matching technique, Int. J. Sci. Engin. (2019).
- [27] Anuradha Thakare , Shubhangi Meshram, H.M. Baradkar, "An Automated Medical Support System For Detecting Human Health Conditions Based On Noval Bicluster Method", I J C T A, Vol.- 10, Issue- 8, Pp. 223- 228, 2017.
- [28] Noriaki Fujishima, Kiyoshi Hoshino, "Fingernail Detection Method From Hand Images Including Palm", Iaprr International Conference On Machine Vision Applications, Pp. 117-120, May 20-23, 2013.
- [29] Hardik Pandit , Dr. D M Shah, "A System For Nail Color Analysis In Healthcare", International Conference On Intelligent Systems And Signal Processing, Pp. 221-223, 2013.
- [30] Mente, R., & Marulkar, S. V. (2017). A review: Fingernail images for disease detection. Int. J. Eng. Comput. Sci, 6(11), 22830-22835.