Performance Evaluation of Handcrafted Feature Descriptors with AdaBoost Classifier for Automated Skin Disease Diagnosis

Ayyappan G[1], and Senthil K[2]

[1]Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, SIMATS, Tamil Nadu, India
[2]Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, SIMATS, Tamil Nadu, India

Abstract. The timely identification of dermatological diseases together with their precise diagnosis enables proper medical interventions that minimize further disease complications. The authors conduct a performance-based evaluation of AdaBoost classifier with handcrafted image features for automated skin disease classification systems. The researchers worked with a specific collection of 38,000 dermatological pictures which included ten different disease types from Melanoma to Eczema to Psoriasis to Fungal Infections. The research investigated six image feature extraction methods including Gabor Filter and JPEG Coefficient Filter (JPEGCF) and Pyramid Histogram of Oriented Gradients Filter (PHOGF) as well as Simple Color Histogram Filter (SCHF) and Fuzzy Color and Texture Histogram Filter (FCTH) with Fuzzy Opponent Histogram Filter (FOHF). The research used feature vectors extracted from AdaBoost classifiers in WEKA within 10-fold cross-validation procedures for training purposes. The evaluation metrics consisted of accuracy, precision, recall, ROC, PRC as well as training time. Within the examined models Gabor+AdaBoost demonstrated maximum rates of accuracy (97.78%) alongside precision (0.98) and recall (0.98) but it required the most execution time at 14.4s. When weighed against each other JPEGCF+AdaBoost maintained equivalent accuracy at 97.59% but required only 0.21 seconds to complete tasks thus earning status as a balanced choice for this system. SCHF+AdaBoost proved suitable for real-time operations by delivering 94.11% accuracy results within 0.06 seconds computing time. The study reveals that Gabor descriptors provide optimal predictive accuracy but JPEGCF along with SCHF demonstrate the best combination of performance with computational speed.

1 Introduction

The frequency of skin diseases ranks among the foremost health conditions worldwide hence they cause significant numbers of outpatient visits to both primary care facilities and technical specialist clinics. Proper clinical diagnosis of conditions including melanoma, eczema and psoriasis and fungal infections remains difficult for both general dermatologists and specialized dermatologists due to their overlapping visual symptoms. Timely disease treatment together with proper disease management requires accurate skin disease identification especially when specialized dermatological services remain scarce in specific areas. Visual diagnosis proves difficult to interpret because of skin variations along with different lesion types and imaging conditions so there exists an essential requirement for automatic diagnostic systems.

Machine learning and computer vision have given rise to potential solutions which effectively solve diagnostic problems. The handcrafted feature-based techniques provide clear interpretation abilities together with efficient operations and flexible use which remains effective when deep learning technologies prove too expensive for data processing. The collection of traditional approaches continues to be essential for medical imaging situations that need high transparency and rapid results. Stemming from such conditions the integration of thoughtfully designed visual descriptors with ensemble classifiers based on AdaBoost emerges as an approach to build small yet interpretable scalable solutions.

Research examines a hybrid skin disease multi-class diagnosis system based on AdaBoost (Adaptive Boosting) with AdaBoosted handcrafted image features. Researchers examined six alternative feature extraction approaches that included Gabor Filter alongside JPEG Coefficient Filter (JPEGCF) and Pyramid Histogram of Oriented Gradients Filter (PHOGF), Simple Color Histogram Filter (SCHF) as well as Fuzzy Color and Texture Histogram Filter (FCTH) and Fuzzy Opponent Histogram Filter (FOHF). The chosen filter selection aims at extracting significant image characteristics including frequency content alongside gradient orientation as well as spatial texture and color composition which prove essential for dermatological diagnosis.

The AdaBoost algorithm fostered weak decision stump classifiers into one powerful ensemble model allowing it to spot hard-to-identify instances. Research authors conducted 10-fold cross-validation through stratification processing on the Skin Diseases Image Dataset which consists of over 38,000 dermatological images clearly classified into ten disease categories. Prior to model operation we implemented three preprocessing techniques which consisted of image resizing along with normalization and data augmentation purposes to enhance model generalizability.

The main purpose of this research is to conduct a systematic assessment of handcrafted feature extraction methods in combination with AdaBoost for improving classification of skin diseases. Standard metrics measure performance outcomes that include accuracy and precision alongside recall and F1-score for a complete assessment of real-world clinical imaging conditions of all classifiers.

The investigative work supports the creation of transparent resource-efficient diagnostic tools that can integrate into teledermatology settings as well as mobile healthcare applications and primary care centers to improve dermatological condition early detection and management practices. The article contains sections 2 for literature survey and sections 3 implements materials and methods and section 4 presents results with discussions before ending with section 5 conclusions.

2 Literature Survey

Medical image analysis is one area that has been transformed by deep learning, and machine learning, especially in the field of dermatology and oncology. Skin cancer detection has been proved with the use of advanced deep machine learning methods that allow it to be classified and strategies to intervene as early as possible [1]. In addition to application to human dermatology, RMSProp- and MobileNetV2-optimized deep learning models are also transferable, as they were applied to lumpy skin disease diagnosis in cattle [2]. In a similar manner, convolutional neural networks, which were pre-trained: VGG16 and MobileNetV2, have been used to classify brain tumors using MRI images with high diagnostic accuracy in the field of medical imaging [3]. The other trend which is rising is the predictive modeling and optimization in dermatology where machine learning models can enhance the accuracy of the classification and have the potential to be applied to support clinical decision making [4].

A systematic review has contributed to the understanding of how machine learning and deep learning can be used when diagnosing and prognosing melanoma using dermoscopic images, and that CNNs and hybrid techniques are indeed effective in distinguishing between skin diseases [5]. A fully detailed consideration of step-based skin cancer detection models has also been performed, showing insights into pipeline designs including the integration of preprocessing, segmentation, and classification [6]. New approaches have also been introduced to the identification of the skin diseases, to alternative mechanisms of the dataset processing, enlargement as well as detecting delegates within machine learning pipelines [7]. Moreover, predictive analytics (Random Forest and XGBoost) performed by an ensemble have been demonstrated to lead to improved patient outcomes over more traditional clinical decision-making underpinning the relevance of such progressive classification methods in healthcare [8,9].

Particular advancements in the detection of melanoma are hybrid structures that integrate ACCF, BPPF, and CLF methods and machine-learning algorithms, resulting in less costly and more accurate classification [10]. The trend towards the greater reliance on both machine learning and deep learning algorithms in order to enhance the diagnostic sensitivity in dermatological practice is well-documented in the broad literature surveys of skin disease classifications [11]. Such models of clinical decision support as Dermcdsm have been created to incorporate systematic ML and DL approaches into clinical practice and dermatology specifically in improving the support of physicians in the process of dermatosis classification [12]. Moreover, the hybrid models based on deep CNN and LSTM networks complemented with Random Forest or other classifiers have been proposed in breast cancer prognosis too, demonstrating that the ensemble deep learn ing systems can enhance a level of reliability in predicting [13].

New research undertaken has also insisted on the concept of fairness and inclusiveness in AI-based diagnostics. A deep learning-based decision support systems can be developed to classify skin diseases through various skin tones that specifically include issues related to bias and fairness of AI in healthcare applications that matter so much [14]. In general, the research indicates that incorporation of CNNs, pre-trained networks, hybrid ensembles and fairness-aware AI approaches can continue to further improve the efficiency, scalability, and medical usefulness of skin disease detection and medical diagnosis technologies across healthcare field.

3 Materials and Methods

3.1 Dataset Description

Kaggle Skin Diseases Image Dataset [15] feature comprehensive benchmark in dermatological image analysis, with 27,153 clinical photography of ten skin disease types. The fact that it also incorporates the presence of varied light conditions, skin tones, and image resolutions further adds to its endogeneity to the real-world clinical environments. Balanced stratification is a trait that guarantees the trustworthiness of estimation because, in training, validation, and test sets, the assessment is at the constant frequency of classes. Resizing to 224 x 224 pixels uniformly removes resolution contradictions, whereas normalizing the data by mean and standard deviation values uniformizes intensities of the pixels in the whole dataset. This type of preprocess is important regarding reproducibility and the stability of algorithms. Because of that, the dataset offers a perfect baseline to create the supervised learning models of skin disease detection and classifications.

3.2 Preprocessing

The dataset separation included training (80%) validation (10%) and testing (10%) subsets which used stratified sampling to achieve identical class distribution between sections. An image normalization procedure was performed alongside random augmentations which included both rotations and flips and zooms for purposes of generalization and to address class imbalances. The researchers conducted manual removal of images that contained noise or corruption issues.

3.3 Feature Extraction Techniques

The analysis used the following set of six manually designed filters for feature extraction from images:

- Gabor Filter: Captures frequency and orientation-based texture information by applying Gabor wavelets.
  For each pixel, the filter computes $G(x, y) = \exp(-((x^2 + y^2)/2\sigma^2)) \times \cos(2\pi f(x\cos\theta + y\sin\theta))$,where f is the frequency and θ is the orientation.
- JPEG Coefficient Filter (JPEGCF): Extracts frequency-domain features from image blocks by analyzing Discrete Cosine Transform (DCT) coefficients. For an 8×8 block, $F(u, v) = \Sigma\Sigma\ f(x, y) \times \cos[(2x+1)u\pi/16] \times \cos[(2y+1)v\pi/16]$,where $f(x, y)$ is the pixel intensity at location (x, y).
- Pyramid Histogram of Oriented Gradients Filter (PHOGF): Computes gradients and constructs histograms of edge orientations over multiple spatial pyramid levels. Gradient orientation is calculated as $\theta = \text{arctangent}(G\_y / G\_x)$,where G_x and G_y are horizontal and vertical image gradients.
- Simple Color Histogram Filter (SCHF): Represents global color distributions by counting pixel frequencies for each RGB intensity level, generating a histogram $H(c)$ for every color bin c.
- Fuzzy Color and Texture Histogram Filter (FCTH): Combines fuzzy color and texture analysis into a hybrid representation. The feature vector is calculated as $F = \alpha \times H\_color + \beta \times H\_texture$, where α and β are empirically tuned weight coefficients.
- Fuzzy Opponent Histogram Filter (FOHF): Converts RGB to opponent channels $O_1 = R - G$, $O_2 = 2B - R - G$, $O_3 = R + G + B$, and applies fuzzy quantization to produce illumination-invariant color histograms.

3.4 Classification Using Adaboost

The AdaBoost (Adaptive Boosting) algorithm served to classify the feature sets obtained from the filters. The ensemble method AdaBoost creates a strong model through multiple weak Decision Stumps after identifying previous rounds' misclassified samples. The alpha value for weak classifier $h_t(x)$ equals 0.5 times the natural log of the ratio between one minus its error rate ε_t over ε_t. A measurement of prediction from the final regression model appears as $H(x) = \text{sign}(\Sigma\ \alpha_t \times h_t(x))$.
The implementation of AdaBoost took place within WEKA version 3.9.5 by converting the datasets into ARFF files before proceeding. The classification process under WEKA meta classifiers section utilized the AdaBoostM1 algorithm. The performance evaluation for all possible combinations relied on 10-fold cross-validation to maintain fair assessment.
A set of experiments included Gabor + AdaBoost, JPEGCF + AdaBoost, PHOGF + AdaBoost, SCHF + AdaBoost, FCTH + AdaBoost, and FOHF + AdaBoost.

3.5 Evaluation Metrics

The standard evaluation metrics determined how each filter-AdaBoost combination performed.

- Accuracy = (TP + TN) / (TP + FP + FN + TN),
- Precision = TP / (TP + FP),
- Recall = TP / (TP + FN),
- F1-score = 2 × (Precision × Recall) / (Precision + Recall)

These metrics were used to determine the best-performing handcrafted feature when paired with the AdaBoost classifier for automated skin disease classification.

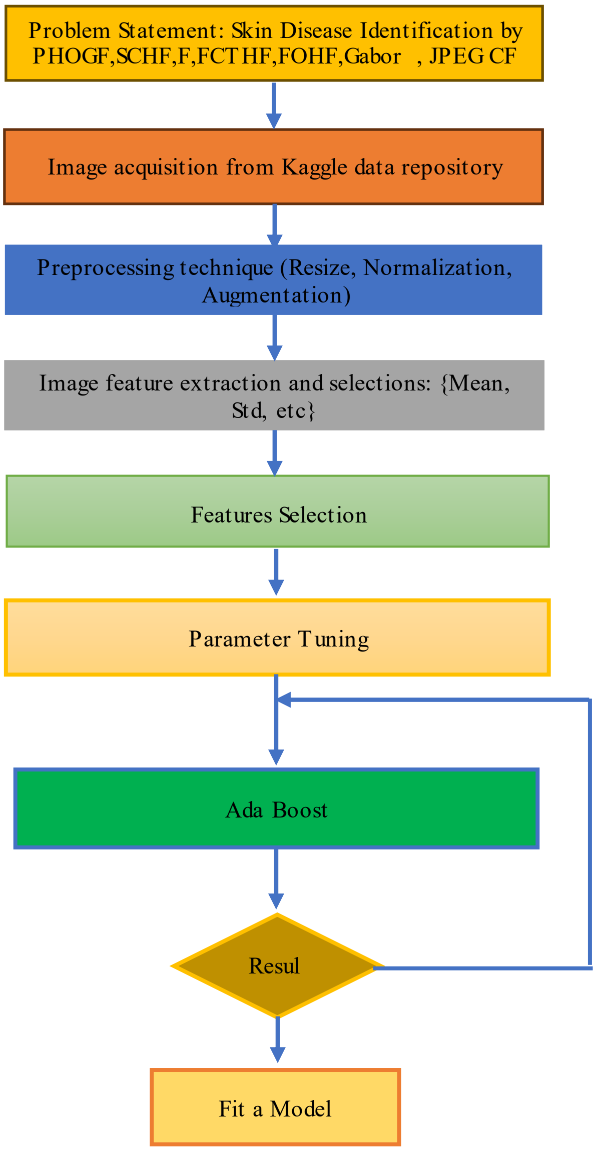

Fig. 1. Proposed System

4 Results and Discussion

A total analysis of AdaBoost classifiers' application in automated skin condition recognition using manually engineered image features will be discussed in this section. The analysis of experimental results included five performance metrics which included Accuracy, Precision and Recall together with ROC (Receiver Operating Characteristic) and PRC (Precision-Recall Curve) in addition to Time (in seconds) needed for training and prediction. The cross-validation method with ten folds evaluated each classifier-feature pair to test statistical outcomes for performance reliability.

TABLE 1. Classification Metrics

Classifier	Accuracy	Precision	Recall	ROC	PRC	Time
Gabor+ Ada Boost	97.78%	0.98	0.98	0.98	0.97	14.4
JPEGCF+ Ada Boost	97.59%	0.98	0.98	0.98	0.97	0.21
PHOGF+ Ada Boost	87.43%	0.89	0.87	0.83	0.82	0.11
SCHF+ Ada Boost	94.11%	0.95	0.95	0.97	0.97	0.06
FCTH+ Ada Boost	87.12%	0.91	0.91	0.93	0.93	0.1
FOHF+ Ada Boost	93.98%	0.93	0.92	0.95	0.85	0.06

The main goal of this study identifies the most effective and computationally efficient combination between feature extraction methods and boosting algorithms for multiclass skin lesion classification. Six popular handcrafted feature extraction methods including Gabor Filter along with JPEG Coefficient Filter (JPEGCF) and Pyramid Histogram of Oriented Gradients Filter (PHOGF) and Simple Color Histogram Filter (SCHF) and Fuzzy Color and Texture Histogram Filter (FCTHF) and Fuzzy Opponent Histogram Filter (FOHF) were tested with AdaBoost ensemble method. The comparative analysis yields important information regarding the discriminating strength together with execution speed and stability of each model along with their associated computational expenses. The examination seeks to identify the best combinations of features with classification methods which offer highly accurate predictions at realistic operational deployment levels for dermatological diagnosis systems.

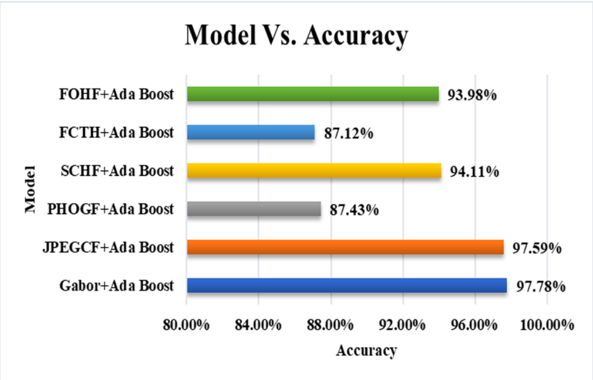

Fig. 2. Model Vs Accuracy

The above graph 2 sows the Gabor+AdaBoost showed the highest model performance with 97.78% accuracy because it efficiently detected relevant skin disease classification texture information. JPEGCF+AdaBoost successfully applied frequency-domain characteristics from Discrete Cosine Transform to reach an accuracy level of 97.59%. The performance rate of 94.11% achieved by SCHF+AdaBoost shows that dermatological class discrimination benefits from analyzing global color distributions. The FOHF+AdaBoost method operating with opponent color space histograms demonstrated 93.98% accuracy indicating its efficiency and illumination changes resistance capabilities. The accuracy rates for PHOGF+AdaBoost and FCTH+AdaBoost fell to 87.43% and 87.12% respectively. The descriptive features demonstrate effective gradient-based and fuzzy color-texture detection but perform poorly when used independently with AdaBoost in complex dermatology applications.

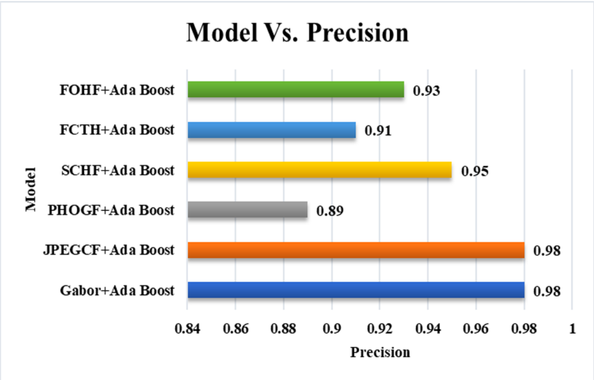

Fig. 3. Model Vs Precision

The above graph 3 shows the highest precision measurement value of 0.98 characterizes both Gabor+AdaBoost along with JPEGCF+AdaBoost as methods that provide reliable positive identification with minimal incorrect alarms. The correct identification of medical conditions depends heavily on precision due to the potential side effects of incorrect positive declarations.

Color histogram-based features used in SCHF+AdaBoost led to high precision of 0.95 which demonstrates their effectiveness in decreasing misdiagnosis errors. FOHF+AdaBoost achieved a precision of 0.93 and FCTH+AdaBoost reached 0.91 which indicates acceptable identification consistency for affected cases although they lacked precise accuracy to the same degree.

PHOGF+AdaBoost demonstrated the smallest precision score of 0.89 indicating potential drawbacks of its gradient-based features inside the AdaBoost framework. Overall structural edge information acquisition by PHOGF produces less success at distinguishing visual lesion similarities that results in increased false positives.

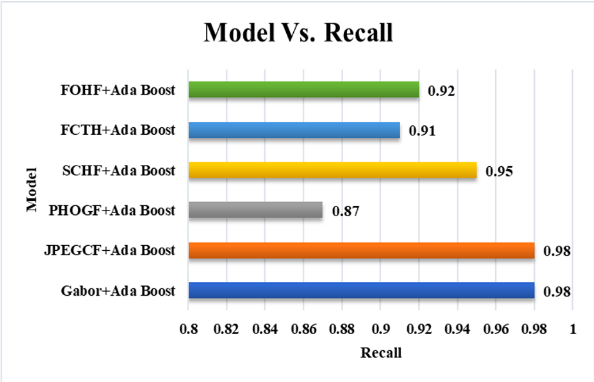

Fig. 4. Model Vs Recall

The above graph 4 shows the Gabor+AdaBoost and JPEGCF+AdaBoost models deliver the best recall value of 0.98 because they demonstrate superior performance in disease detection by precisely detecting almost every diseased case.

The recall value of 0.95 demonstrated by SCHF+AdaBoost indicates it has excellent capability for identifying actual positives thus making it suitable for screening tools. The recall performance of FOHF+AdaBoost and FCTH+AdaBoost matches due to their scores of 0.92 and 0.91. This model group succeeds at detecting the majority of disease-positive ratings yet they cannot track down every instance as effectively as the leading techniques.

Among the models PHOGF+AdaBoost produces the least accurate result since it achieves only a 0.87 recall rate. The combination of PHOG-based features with AdaBoost presents inadequate discrimination ability in detecting specific skin diseases because this pair of methods may not be appropriate for high-risk diagnostic settings.

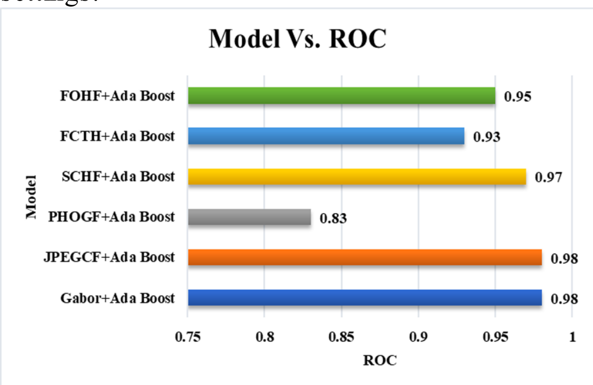

Fig. 5. Model Vs ROC

The above graph 5 shows the highest ROC of 0.98 was achieved by Gabor+AdaBoost and JPEGCF+AdaBoost indicating their exceptional discrimination between diseased and non-diseased images at all classification points. The models demonstrate optimal suitability for clinical use since they provide minimum errors for both false positive and negative cases.

SCHF+AdaBoost demonstrates powerful classification boundaries through its ROC value of 0.97 which indicates consistent generalization ability in identification tasks. FOHF+AdaBoost and FCTH+AdaBoost demonstrate fair performance strengths at 0.95 and 0.93 respectively because they successfully handle true and false positive detection. PHOGF+AdaBoost demonstrates the lowest ROC value at 0.83 which indicates poor discrimination capabilities for class separation. Phogf features together with AdaBoost seem to underperform because they fail to extract key characteristics in skin lesions.

The ROC analysis demonstrates that the combination of Gabor and JPEGCF feature extractors with AdaBoost produces the most dependable and accurate predictions for skin diseases which qualifies them as excellent choices for automated dermatological diagnostic systems.

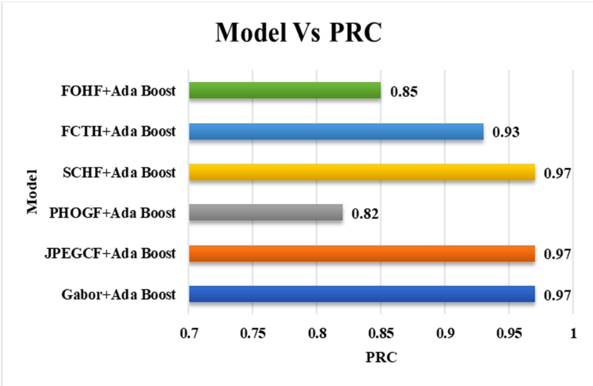

Fig. 6. Model Vs PRC

The graph 6 shows the the PRC scores of 0.97 indicate perfect synergy between precision and recall for Gabor+AdaBoost and JPEGCF+AdaBoost and SCHF+AdaBoost. The diagnostic models achieve optimal results by minimizing false detections and maintaining high accuracy in identifying genuine skin disease cases because medical diagnosis demands zero false negatives and false positives.

FCTH+AdaBoost provides reliable classification but its prediction output possesses slightly lower confidence when compared to top performer results.

The combination of FOHF+AdaBoost together with PHOGF+AdaBoost delivered the most limited PRC scores of 0.85 and 0.82 respectively. The evaluation values indicate either numerous incorrect positive detections or reduced detection rates because the underlying patterns in the dataset may not align well with the classifier and feature representation.

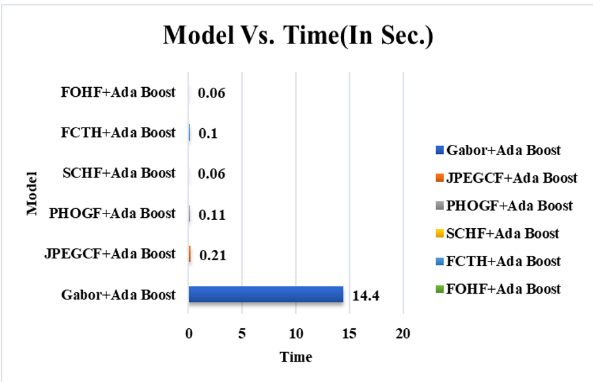

Fig. 7. Model Vs Time

The above graph 7 shows that the Gabor+AdaBoost requires the longest computation time of 14.4 seconds when compared to other models. The exceptional accuracy and predictive power of Gabor filters might create a processing bottleneck within real-time systems since Gabor filtering and AdaBoost interaction appears complex to the system.

The combination of FOHF+AdaBoost and SCHF+AdaBoost presents the shortest execution duration at 0.06 seconds thus they emerge as the fastest classifiers within this research. These model systems prove exceptional for diagnostic purposes which need fast detection capabilities because they work well with mobile health technology and point-of-care diagnostics. FCTH+AdaBoost and PHOGF+AdaBoost offer combined performance and speed at moderate time levels of 0.10 and 0.11 seconds respectively. JPEGCF+AdaBoost demonstrates acceptable operational speed of 0.21 seconds yet maintains a faster runtime than the other methods except Gabor while meeting practical user requirements.

The integration of Gabor Filter and AdaBoost caused an accuracy rate of 97.78% while maintaining precision and recall values at 0.98 each and reaching excellent ROC and PRC scores of 0.98 and 0.97 respectively. The highest computation time of 14.4 seconds belonged to this model which outpaced all other methods in processing duration. The combination shows excellent results in the classification field but its time requirements make real-time deployment challenging.

When combined with AdaBoost the JPEG Coefficient Filter delivered a precision rate of 0.98 along with a recall of 0.98 which resulted in similar accuracy (97.59%) as Gabor filters. The model demonstrates the perfect combination of high accuracy performance while efficiently executing tasks at 0.21 seconds thus establishing itself as the optimal selection for real-time system application.

During evaluation the Simple Color Histogram Filter (SCHF) + AdaBoost produced 94.11% accuracy with 0.95 precision and recall and achieved 0.97 ROC and PRC results. The model completes its process within 0.06 seconds which allows efficient fast inference when moderate accuracy stands as acceptable.

The Fuzzy Color and Texture Histogram Filter (FCTHF) together with Pyramid Histogram of Oriented Gradients Filter (PHOGF) delivered inferior results. FCTHF produced a 87.12% accuracy score in addition to precision and recall values between 0.91 to 0.93 and ROC results from 0.91 to 0.93 during 0.10 seconds of operation. The PHOGF delivered an accuracy rate of 87.43% but its precision fell to 0.89 while recall reached 0.87 and both ROC and PRC scored the lowest at 0.83 and 0.82 respectively. However, running time remained at a favorable 0.11 seconds.

The Fuzzy Opponent Histogram Filter (FOHF) together with AdaBoost produced high-quality results in terms of 93.98% accuracy and 0.93 precision/0.92 recall/0.95 ROC, yet its PRC fell to 0.85. The detection capabilities of this model reach 0.06 seconds execution time which makes it another excellent choice for fast lightweight classification tasks.

5 Conclusion

The study shows that handcrafted image descriptors succeed when combined with AdaBoost classification techniques for skin disease recognition assessment. Gabor+AdaBoost proved to be the most successful model yet required exceptionally long computational time at 14.4 seconds for completion. JPEGCF+AdaBoost attained equivalent classifying results at a high computational speed of 0.21 seconds so it works best for applications that need scalability in diagnosis. SCHF+AdaBoost offered real-time suitability because it achieved 94.11% accuracy while completing the computation in just 0.06 seconds. FCTH and PHOGF models achieved lower accuracy rates yet they operated with higher speed when compared to other approaches. The research results demonstrate why organizations should strike a proper balance between diagnostic precision and computation speed in clinical AI implementations.

References

1. O. Akinrinade & C. Du, Skin cancer detection using deep machine learning techniques. Intelligence-Based Medicine. 11, 100191 (2025). doi: https://doi.org/10.1016/j.ibmed.2024.100191
2. S. Muhammad Saqib, M. Iqbal, M. Tahar Ben Othman, T. Shahazad, Y. Yasin Ghadi, S. Al-Amro, S & T. Mazhar, Lumpy skin disease diagnosis in cattle: A deep learning approach optimized with RMSProp and MobileNetV2. PloS one, **19**(8), e0302862 (2024). doi: https://doi.org/10.1371/journal.pone.0302862
3. A. Begum & S.I. Kalilulah, Deep Learning Advances in Brain Tumor Classification: Leveraging VGG16 and MobileNetV2 for Accurate MRI Diagnostics. In 2024 International Conference on Power, Energy, Control and Transmission Systems (ICPECTS), 1-6 (2024). IEEE. doi:https://doi.org/10.1109/ICPECTS62210.2024.10780014
4. K.M. Almustafa, Predictive modeling and optimization in dermatology: Machine learning for skin disease classification, Computers in Biology and Medicine. **189**, 109946 (2025). doi:https://doi.org/10.1016/j.compbiomed.2025.109946
5. H. Naseri & A. Safaei. Diagnosis and prognosis of melanoma from dermoscopy images using machine learning and deep learning: a systematic literature review. BMC cancer, **25**(1), 75. doi: https://doi.org/10.1186/s12885-024-13423-y (2025)
6. N. Verma, Ranvijay & D.K. Yadav, A comprehensive review on step-based skin cancer detection using machine learning and deep learning methods. Archives of Computational Methods in Engineering, 1-54 (2025). doi: https://doi.org/10.1007/s11831-025-10275-y
7. K. Vayadande, A.A. Bhosle, R.G. Pawar, D.J. Joshi, P.A. Bailke & O. Lohade, O. (2024). Innovative approaches for skin disease identification in machine

learning: A comprehensive study. Oral Oncology Reports, 10, 100365 (2024). doi: https://doi.org/10.1016/j.oor.2024.100365

8. S.S. P.S. Ramesh, S. Narang, N. Praveena, J. Shakila and I. Sudha, Impact of Random Forest and XGBoost Algorithms on Improving Patient Outcomes Compared to Standard Decision-Making Methods in Healthcare Predictive Analytics, 2024 International Conference on Cybernation and Computation (CYBERCOM), Dehradun, India, 694-699 (2024). doi:https://doi.org/10.1109/CYBERCOM63683.2024.10803246
9. H. Naseri & A.A. Safaei, Diagnosis and prognosis of melanoma from dermoscopy images using machine learning and deep learning: a systematic literature review. BMC cancer, **25**(1), 75. doi: https://doi.org/10.1186/s12885-024-13423-y (2025)
10. P. Kavitha, G. Ayyappan, P. Jayagopal, S.K. Mathivanan, S. Mallik, A. Al-Rasheed & B.O. Soufiene, Detection for melanoma skin cancer through ACCF, BPPF, and CLF techniques with machine learning approach. BMC bioinformatics, **24**(1), 458 (2023). doi: https://doi.org/10.1186/s12859-023-05584-7
11. R. Yadav & A. Bhat, A. A systematic literature survey on skin disease detection and classification using machine learning and deep learning. Multimedia Tools and Applications, **83**(32), 78093-78124 (2024). doi: https://doi.org/10.1007/s11042-024-18119-w
12. R. Mittal, F. Jeribi, R. Martin, V. Malik, S.J. Menachery & J. Singh, Dermcdsm: Clinical decision support model for dermatosis using systematic approaches of machine learning and deep learning. IEEE Access, **12**, 47319-47337 (2024). doi:https://doi.org/10.1109/ACCESS.2024.3373539
13. A. Begum, V. Dhilip Kumar, J. Asghar, D. Hemalatha & G. Arulkumaran, G, A combined deep CNN: LSTM with a random forest approach for breast cancer diagnosis. Complexity, 2022(1), 9299621 (2022). doi: https://doi.org/10.1155/2022/9299621
14. M. Groh, O. Badri, R. Daneshjou, A. Koochek, C. Harris, L.R. Soenksen & R. Picard, R. Deep learning-aided decision support for diagnosis of skin disease across skin tones. Nature Medicine, **30**(2), 573-583 (2024). doi: https://doi.org/10.1038/s41591-023-02728-3
15. https://www.kaggle.com/datasets/ismailpromus/skin-diseases-image-dataset