Journal of Information & Optimization Sciences
ISSN 0252-2667 (Print), ISSN 2169-0103 (Online)
Vol. 47 (2026), No. 5-B, pp. 2095–2107
DOI : 10.47974/JIOS-2300

Improvised deep learning techniques with the spectral concept for the robust skin disease image classification

Lakshmi Deepthi Nukala *
T. Aruna Sri †
Department of Computer Science and Engineering
Koneru Lakshmaiah Education Foundation
Hyderabad 500075
Telangana
India

K. Rajendra Prasad §
Department of Computer Science & Engineering
Amity University Hyderabad
Hyderabad 500108
Telangana
India

Abstract

In the field of medical research on skin diseases, machine learning categorization approaches are becoming increasingly prominent. The classification process frequently makes use of the extraction of visual features based on statistical analysis. Statistically-based image feature extraction approaches are not as effective as deep models, which are learned skin images. Examples of deep models include convolutional neural networks, Mobilenet, Resnet, Densenet, and GoogleNet. Deep models are employed to locate features more efficiently. There are several concerns with deep features, including those that pertain to the curse of dimensionality and data sparsity issues. The spectral notion that is utilized for the purpose of locating the lower manifold subspace of deep features is successfully handled by subspace learning techniques, which are the most successful methods for dealing with the curse of dimensionality. There was also a reduction in the data sparsity impact that occurred throughout the process of translating a high-dimensional subspace into a lower manifold space. By locating the principal components, also known as principal Eigenvectors, it is possible to acquire equivalent spectral features. In comparison to the dimensions of deep features, the number of primary components is substantially lower. The process of

* *E-mail:* lakshmideepthi16@gmail.com (Corresponding Author)
† *E-mail:* talluriaruna18@gmail.com
§ *E-mail:* krprgm@gmail.com

© Taru Publications

mapping the deep features onto the spectral (or Eigen) lower manifold space is referred to as the spectral space. This process is effective in preserving the information contained in the skin image data. In order to achieve robust skin disease classification, the work that is being proposed expands the deep-based classifier techniques by using the spectrum notion. Through the utilization of the benchmarked dermoscopic and clinical image datasets, the experimental investigation demonstrates the effectiveness of the offered methodologies.

Subject Classification: *Primary 68U15, Secondary 68U35.*

Keywords: *Deep models, Skin classification, Spectral concept, Data sparsity, Curse of dimensionality.*

1. Introduction

In the field of skin healthcare research, deep learning algorithms have demonstrated significant advancements [1]. A new approach to the classification of skin lesions is being developed in the field of skin healthcare: dermatoscopy [2]. A distinct region of the skin that is afflicted by infections is referred to as a skin lesion. The skin lesion should be diagnosed as soon as possible in order to assist prevent significant cancer complications. For the purpose of enhancing the precision of diagnosis and the identification or categorization of skin illnesses, the field of dermatology relies heavily on approaches that involve machine learning and deep models. The Gray-Level Co-Occurrence Matrix (GLCM) [3] is a well-known texture analysis method that has been successful in skin image classification. This technique is used in image processing statistical modeling. When the image data is on a smaller size, its computations transform into a more basic process. The classification procedure is slowed down in other instances because it encounters more serious dimensionality difficulties. Digitized analysis that is automated provides dermatologists with the ability to diagnose and detect skin cancer more effectively. When it comes to research on skin healthcare, the GLCM and other pertinent image-processing statistical approaches [4] have seen extensive application over the course of the past two decades. The approaches of machine learning, which include random forest (RF), support vector classifier (SVC), and k-nearest neighbor (kNN) [5], are highly suggested for the purpose of reaching the desired classifications of skin diseases. This classification of skin diseases is significantly impacted by the pre-processing and feature extraction procedures that are utilized. Real-time skin categorization results in automated healthcare systems are achieved by the utilization of a mix of GLCM-based feature extraction and machine learning algorithms, as demonstrated in research [6]. The extensive

calculations of GLCM are responsible for the excellent results that the machine learning approaches that are based on GLCM achieve for the limited range of image datasets. In spite of this, efficient modeling necessitates the training of a vast dataset in order to yield images that are classified as skin diseases. Regarding big image collections, the visual examination and detection of skin lesions has become a tough subject to deal with. As time goes on, deep models are becoming increasingly appealing, particularly for applications that involve image processing. Traditional classifier methods, such as SVC, kNN, Random Forest [7], and others, are rendered obsolete by the advent of massive image training with deep models. For real-time medical applications, convolutional neural networks (CNNs), MobileNet, GoogleNet, and Densenet [8] are useful tools to have at your disposal. Alsahafi, Kassem, and Hosny [1] proposed the residual deep convolution network with cross-channel correlation.

The term "spectral space" refers to the space that is obtained by the principal components (also known as Eigenvectors) of the lower manifold. The study that is being offered was created with two primary stages: i) locating the spectrum projected space of deep features, and ii) utilising classifier approaches for the purpose of effectively classifying skin lesions. There is research conducted in [11] on the following deep learning methodologies: Both the residual deep convolution neural network and the cross-channel correlation were utilized. The concept of cross-correlation is also referred to as a sliding dot product. The cross-correlation technique is used to determine the degree of similarity between different parts of a single image. The procedure known as cross-correlation involves moving a filter mask over the image and computing the total of products at each place. In order to address the issue of the imbalanced dataset, the dataset was transformed into a vector consisting of images and weights rather than images and labels [9]. However, any modification to the photos that make up the dataset may result in weight modifications, which may result in the weights being reproduced once more. Due to the fact that cross-channel causes the size of the feature vector to expand, this deep model is not considered to be lightweight [10]. As a result, there are some restrictions, such as the amount of time it takes to run, and the approach is not lightweight. The statistical image processing methods described in [12] (Gray Level feature Co-occurrence matrix -GLCM with contrast, energy, entropy, correlation, and homogeneity) are utilized for the purpose of extracting features from skin images. Subsequently, the techniques of SVM, KNN, and Decision Tree are utilized for the classification of skin

disease images. Classifier algorithms that are based on image statistical techniques (GLCM statistical) offer good classification results. On the other hand, retrieved features based on deep learning provide effective discriminative lesions of skin photos. When compared to GLCM statistical features, deep features provide a greater amount of spatial information for the skin images. The authors of [4] provide deep convolutional neural networks as a means of identifying the more distinguishable characteristics of skin photographs in order to enhance the detection rate of skin illness identification. Following the extraction of 128-dimensional features (embeddings) from training samples into Euclidean space, the next step is to compute L-2 distances between corresponding images by making use of the embeddings that have been learned. The two-stage process of the proposed work is shown in Figure 1.

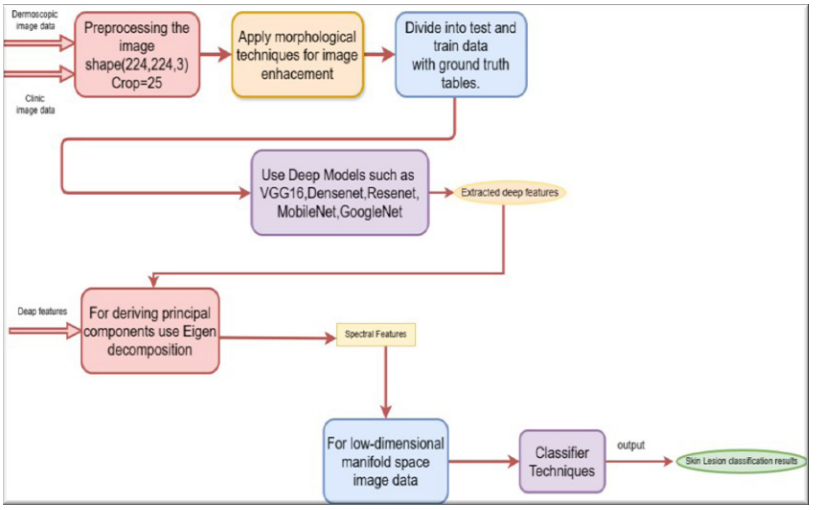


Figure 1

Two-Stage Deep Spectral-Based Classifier Model

Key contributions of the work are summarized as follows:

1. Pre-processing the images of the skin diseases, such as cropping, resizing, and training and testing images.
2. Finding the lower manifold principal components of the deep features by implementing the spectral deep model
3. Develop the hybrid deep spectral-based classifier models for efficient skin lesion classification

2. Literature Study

A significant part of real-time skin healthcare applications is the detection of skin cancers [20] through the examination of the spatial characteristics of photographs of the skin. For medical applications in society, it is necessary to identify severe infections and conduct accurate analyses of skin malignancies. An accurate identification of skin illnesses is achieved through the utilization of two distinct types of skin images, namely dermoscopic and clinical imaging. There is a growing trend among medical practitioners and senior physicians to automate the classification of skin diseases or tumors on the skin. Because there is a lack of sophisticated and macro analysis, manual skin lesion classification in the early stages is notoriously difficult. The application of statistical spatial analytic methods and algorithmic approaches to machine learning led to substantial advancements in skin healthcare research, which resulted in important innovations and outcomes. Basal cell carcinoma (BCC), blue nevus (BN), melanoma, melanosis, seborrheic keratosis (SK), and vascular lesions (VL) are an example of the skin lesions that are considered to be among the most serious skin conditions. There are databases of photos of skin lesions and their metadata that are available to the public in [11]. These datasets include both dermoscopic and clinic images showing skin lesions. Skin infections pose a significant risk since they can lead to the development of cancer in the major tissues. The extracted features of skin disease photographs need to be looked at in order to conduct an analysis of these cases. Skin lesions can be classified using this deep model of ResNet54 with cross-channel correlation, and it does so without any problems of overfitting. Furthermore, the classification results that it produces are quite appealing. The problem of imbalanced data is efficiently addressed by this methodology, which takes into consideration the dataset in terms of images and weights rather than images and labels. As a result, its computations are complicated, and the model needs to be made more lightweight; also, it necessitates a longer amount of computing time for the classification of skin lesions. Through the development of innovative deep learning models, such as ResNet152 and the Inception ResNet-V2 model, the article [24] proposes that advancements can be made in the classification of skin lesions. Image learning is gained in Euclidean space in these models, and the L-2 distances between the images are computed. The article [14] discusses a number of recent developments in the field of skin healthcare research that involve machine learning and deep learning

approaches. It is essential to discover an alternate method of representing deep features in order to overcome the problem of dimensionality.

Recent studies have explored various hybrid machine learning and deep learning approaches for skin disease classification [3], [13], [16]–[19]. These methods highlight the importance of feature extraction, dimensionality reduction, and efficient classification techniques in medical image analysis. Several review works also emphasize the challenges of handling high-dimensional data and improving classification accuracy in healthcare applications [21]–[23].

3. Proposed Deep-Based Fusion Models

A presentation of deep spectral-based classifier models that have been proposed is included in this section. The following is a description of the processes that comprise its methodology: pre-processing the skin images, extraction of deep characteristics, discovery of the Eigenspace (or spectral space), and categorization of skin lesions. In the beginning, the pre-processing of the photographs is carried out by ensuring that the image sizes are consistent throughout. The area of interest (ROI) technique is used to locate the precise location of lesions in skin scans, and the bounding size of the ROI is significantly reduced. The crop operations were able to reduce the return on investment (ROI) of skin lesions and surrounding skin sections. The classification of skin lesions may also be significantly impacted by image enhancement in a significant way. Both the deep training and testing data features are saved in their respective variables, which are referred to as trained_features and test_features respectively. Algorithm 1 contains a presentation of these stesps. The deep features of these datasets are utilized as heavy and excellent features, which include the data sparsity values and are employed to represent them. As a result of the extensive amount of deep learning learning parameters, there is a significant possibility of obtaining sparsity values in both the training and testing features. When it comes to identifying skin lesion datasets, subspace learning is necessary in order to alleviate the problem of data sparsity. In order to address the issue of data sparsity and find a solution to the problem of the curse of dimensionality, subspace learning is required. For efficient subspace learning that does not lead to the loss of any significant cues or features, the Eigen-based lower manifolds space is proposed. The inconsequential characteristics of skin lesions are disregarded by it. The hybrid classification models, also known as deep spectral-based classification models, according to the statement. In

particular, deep-spectral-based RF (DS-RF), deep-spectral-based SVC (DS-SVC), and deep-spectral-based kNN (DS-kNN) are proposed in this study for the purpose of making skin lesion categorization more effective

4. Result Analysis and Discussion

The skin lesion datasets are derived from [18] which are benchmark datasets freely available to the public. The photographs of prominent skin lesions considered in the experimental study are shown in Table 1. The performance comparison graphs are illustrated in Fig. 2(a)–2(l) from Table 2. Accurate classification of skin lesions is essential for the successful diagnosis of skin cancer.

Table 1

Skin Lesion Datasets Description

S. No.	Name of the Dataset	No. of Classes	Size of Data
1	Derm7pt [15]	5	
2	Skin Cancer MNIST HAM10000 [26]	7	9958
3	ISIC 2019 [27], [28]	9	25331

Table 2

Performance Comparison between Deep-based Classifier Models and Deep-Spectral based Classifier Models for Derm7pt Datasets

Performance Measure	Models	Deep Random Forest	DS-RF	Deep-SVC	DS-SVC	Deep-KNN	DS-KNN
Accuracy	Densenet	0.8075	0.8143	0.5744	0.582	0.8554	0.938
	Googlenet	0.772	0.7543	0.5644	0.5744	0.8429	0.9229
	Mobilenet	0.7771	0.7771	0.7771	0.572	0.572	0.9154
	Resenet	0.7999	0.8042	0.5644	0.6404	0.8024	0.9099
	VGG16	0.7568	0.7644	0.6429	0.6657	0.7239	0.8968
Precision	Densenet	0.7516	0.7605	0.3174	0.4098	0.8572	0.9118
	Googlenet	0.7271	0.7238	0.3174	0.319	0.7553	0.9011
	Mobilenet	0.7312	0.745	0.3174	0.45	0.7231	0.8598
	Resenet	0.7451	0.7561	0.3182	0.5238	0.732	0.781
	VGG16	0.7157	0.7244	0.5372	0.6433	0.6223	0.7007

Contd...

Recall	Densenet	0.8075	0.8543	0.5644	0.572	0.8454	0.938
	Googlenet	0.772	0.7843	0.5644	0.5644	0.8429	0.9254
	Mobilenet	0.7771	0.7771	0.5644	0.572	0.8252	0.9174
	Resenet	0.7999	0.8042	0.5644	0.6404	0.8024	0.8999
	VGG16	0.7568	0.7644	0.6429	0.6657	0.7239	0.8568
F-Score	Densenet	0.7547	0.766	0.4055	0.4253	0.7928	0.9244
	Googlenet	0.7002	0.711	0.4055	0.4068	0.7912	0.917
	Mobilenet	0.6994	0.6959	0.4055	0.4237	0.761	0.9034
	Resenet	0.7467	0.6748	0.4062	0.5542	0.7331	0.906
	VGG16	0.6862	0.6871	0.5513	0.5916	0.6538	0.8914

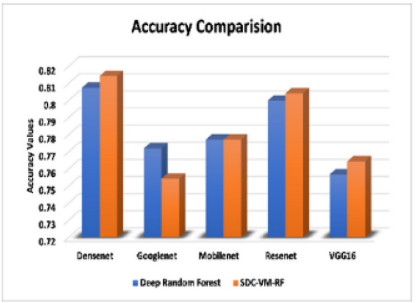


Figure 2(a)

Accuracy between Deep-RF and Deep Spectral RF

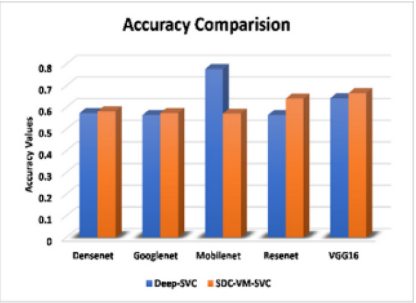


Figure 2(b)

Accuracy between Deep-SVC and Deep Spectral SVC

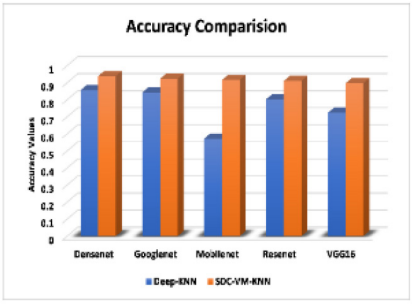


Figure 2(c)

Accuracy between Deep-KNN and Deep Spectral KNN

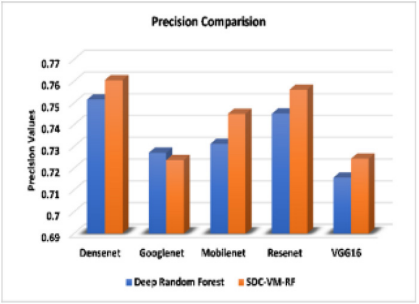


Figure 2(d)

Precision between Deep-RF and Deep Spectral RF

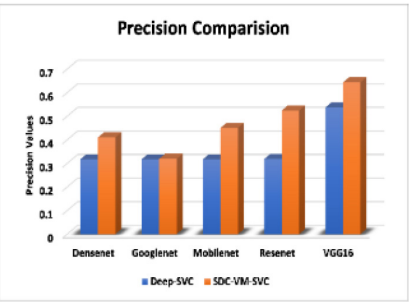


Figure 2(e)

Precision between Deep-SVC and Deep Spectral SVC

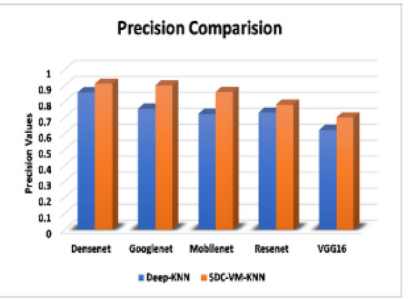


Figure 2(f)

Precision between Deep-KNN and Deep Spectral KNN

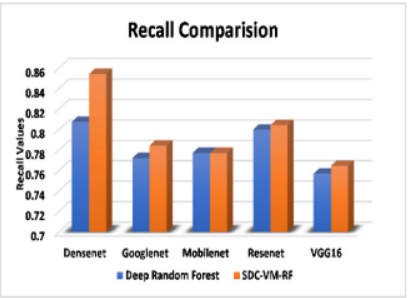


Figure 2(g)

Recall between Deep-RF and Deep Spectral RF

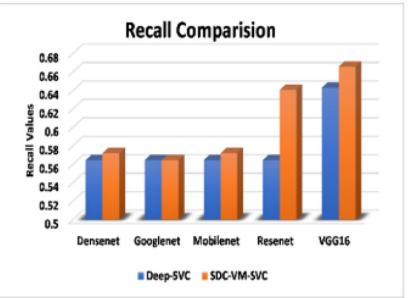


Figure 2(h)

Recall between Deep-SVC and Deep Spectral SVC

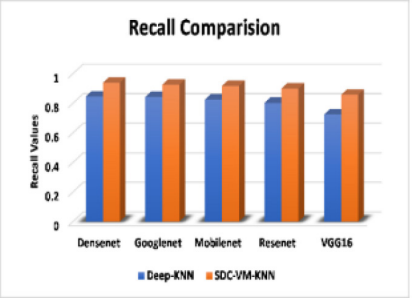


Figure 2(i)

Recall between Deep-KNN and Deep Spectral KNN

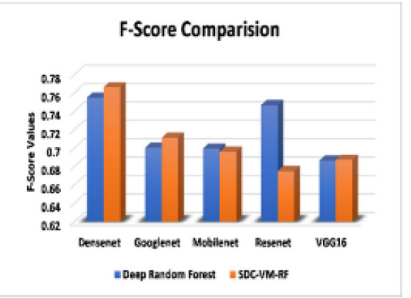


Figure 2(j)

F-Score between Deep-RF and Deep Spectral RF

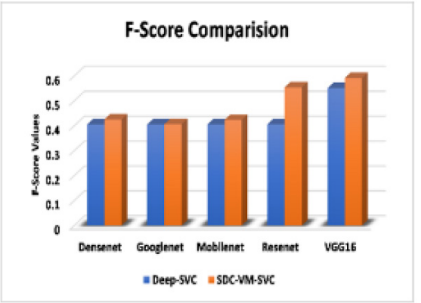


Figure 2(k)

F-Score between Deep-SVC and Deep Spectral SVC

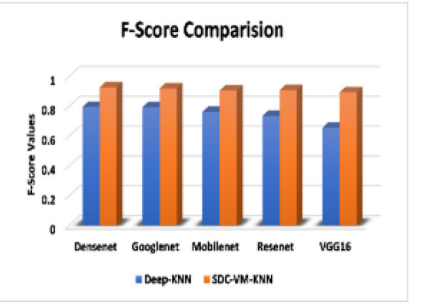


Figure 2(l)

F-Score between Deep-KNN and Deep Spectral KNN

Figure 2

Comparison graphs Classifier Models for Derm7pt Dataset

The automation of classification and early diagnosis is becoming increasingly important in the field of skin healthcare. Advanced deep learning architectures and residual network models have shown significant improvements in classification performance [25], [26]. When comparing the suggested deep spectral-based classifier models to the deep-based classifier models that are already in existence, four performance measures, including accuracy, precision, recall, and f-score, are utilized for the purpose of evaluation.

5. Conclusion and Future Scope

A spectral view of learning was utilized in the suggested methodology, and the best subspace for high-dimensional deep features was established as a result. In order to address the dimensionality problem that is associated with deep features, the deep spectral-based classifier models, such as DS-RF, DS-SVC, and DS-KNN, have been proposed. During the process of learning skin data, the deep characteristics are translated into the ideal subspace. There is less data sparsity in the subspace, and all of the features of the skin data are mapped into the manifolds that have lower dimensions. By resolving the issue4 of data sparsity, the performance values of the models that have been proposed have been expanded. In comparison to the deep-based classifier models that were already in use, the presented models showed a significant improvement in performance values, namely in terms of accuracy, precision, recall, and f-score, with a

rate of 18 to 22%. Using a single view subspace learning framework, these proposed approaches were able to produce the classification findings. Finding a way to classify skin lesions using multi-view learning (that is, learning deep features in many subspaces) is the next step in the work that will be done in order to optimize performance even more.

References

[1] Y. S. Alsahafi, M. A. Kassem, and K. M. Hosny, "Skin-Net: A novel deep residual network for skin lesions classification using multilevel feature extraction and cross-channel correlation with detection of outlier," *J. Big Data,* vol. 10, no. 105 (2023).

[2] M. Ahammed, M. A. Mamun, and M. S. Uddin, "A machine learning approach for skin disease detection and classification using image segmentation," *Healthcare Analytics*, vol. 2 (2022).

[3] M. Q. Hatem, "Skin lesion classification system using a K-nearest neighbor algorithm," *Vis. Comput. Ind. Biomed.*, vol. 5, no. 7 (2022).

[4] B. Ahmad, M. Usama, C. M. Huang, K. Hwang, M. S. Hossain, and G. Muhammad, "Discriminative feature learning for skin disease classification using deep convolutional neural network," *IEEE Access*, vol. 8, pp. 39025–39033 (2020).

[5] G. Yang, S. Luo, and P. Greer, "Advancements in skin cancer classification: A review of machine learning techniques in clinical image analysis," *Multimed. Tools Appl*. (2024).

[6] K. Vayadande, A. A. Bhosle, R. G. Pawar, D. J. Joshi, P. A. Bailke, and O. Lohade, "Innovative approaches for skin disease identification in machine learning: A comprehensive study," *Oral Oncol. Rep*., vol. 10 (2024).

[7] S. G. Malik, S. S. Jamil, A. Aziz, S. Ullah, I. Ullah, and M. Abohashrh, "High-precision skin disease diagnosis through deep learning on dermoscopic images," *Bioengineering*, vol. 11, no. 867 (2024).

[8] R. Sadik, A. Majumder, A. A. Biswas, B. Ahammad, and M. M. Rahman, "An in-depth analysis of convolutional neural network architectures with transfer learning for skin disease diagnosis," *Healthcare Analytics*, vol. 3 (2023).

[9] M. Li, Y. Jiang, Y. Zhang, and H. Zhu, "Medical image analysis using deep learning algorithms," *Front. Public Health*, vol. 11 (2023).

[10] D. Matsuoka, "Classification of imbalanced cloud image data using deep neural networks: Performance improvement through a data science competition," *Prog. Earth Planet. Sci.*, vol. 8, no. 68 (2021).

[11] M. H. Abid, R. Ashraf, T. Mahmood, and C. M. N. Faisal, "Multimodal medical image classification using deep residual network and genetic algorithm," *PLoS ONE*, vol. 18, no. 6 (2023).

[12] Z. Abbas, M. Rehman, S. Najam, and S. M. Rizvi, "An efficient gray-level co-occurrence matrix (GLCM) based approach towards classification of skin lesion," in *Proc. AICAI,* pp. 317–320 (2019).

[13] S. Verma and M. Kumar, "A hybrid machine learning model for skin disease classification using discrete wavelet transform and gray level co-occurrence matrix," *Multimed. Tools Appl*. (2024).

[14] J. Zhang,"Recent advancements and perspectives in the diagnosis of skin diseases using machine learning and deep learning: A review," *Diagnostics, vol.* 13, no. 3506 (2023).

[15] P. Tschandl, "The HAM10000 dataset: A large collection of multi-source dermatoscopic images of common pigmented skin lesions," (2018).

[16] S. K. Bandyopadhyay, P. Bose, A. Bhaumik, and S. Poddar, "Machine learning and deep learning integration for skin diseases prediction," *Int. J. Eng. Trends Technol.*, vol. 70, no. 3, pp. 13–21 (2022).

[17] M. A. Kassem, K. M. Hosny, R. Damaševičius, and M. M. Eltoukhy, "Machine learning and deep learning methods for skin lesion classification and diagnosis: A systematic review," *Diagnostics*, vol. 11, no. 1390 (2021).

[18] R. Miotto, F. Wang, S. Wang, X. Jiang, and J. T. Dudley, "Deep learning for healthcare: Review, opportunities and challenges," *Brief Bioinform.*, vol. 19, no. 6, pp. 1236–1246 (2018).

[19] B. Gunasundari and R. Thiagarajan, "Evaluation of high-dimensional data classification for skin malignancy detection using DL-based techniques," *Cancer Investigation*, vol. 42, no. 5, pp. 365–389 (2024).

[20] M. A. Kadampur and S. A. Riyaee, "Skin cancer detection: Applying a deep ulearning-based model driven architecture in the cloud for classifying dermal cell images," *Informatics Med. Unlocked*, vol. 18 (2020).

[21] A. Mohammed and R. Kora, "A comprehensive review on ensemble deep learning: Opportunities and challenges," *J. King Saud Univ. Comput. Inf. Sci*., vol. 35, no. 2, pp. 757–774 (2023).

[22] A. Khan, A. Sohail, U. Zahoora, and A. S. Qureshi, "A survey of the recent architectures of deep convolutional neural networks," *Artif. Intell. Rev.*, vol. 53, pp. 5455–5516 (2020).

[23] N. Hasan, M. A. Khatun, M. A. Islam, M. S. Rahman, M. A. Hossain, and M. R. Islam, "Skin cancer: Understanding the journey of transformation from conventional to advanced treatment approaches," *Mol. Cancer,* vol. 22, no. 168 (2023).

[24] S. M. Kadham and M. A. Mustafa, "Fuzzy SHmath.Mbio-transform generalization and application to skin cancer imaging (distributed diseases)," *Journal of Interdisciplinary Mathematics*, vol. 26, no. 6, pp. 1031–1042 (2023), doi: 10.47974/JIM-1603.

[25] G. K. Yadav, A. K. Tiwari, V. K. Singh, A. Kumar, D. Varshney, and A. K. S. Senger, "Empirical algorithm to detect skin disease using deep convolution neural networks through MobileNet algorithm," *Journal of Information and Optimization Sciences,* vol. 45, no. 4, pp. 1017–1027 (2024), doi: 10.47974/JIOS-1624.

[26] M. A. Babu, M. M. Ahmmed, A. Ferdousi, M. M. Rahman, M. Saiduzzaman, and V. Bhatnagar, "The mathematical and machine learning models to forecast the COVID-19 outbreaks in Bangladesh," *Journal of Interdisciplinary Mathematics,* vol. 25, no. 3, pp. 753–772 (2022).

[27] M. K. Gupta, P. Dadheech, A. Kumar, S. R. Dogiwal, R. C. Poonia, L. Raja, and D. P. Bhatt, "Detection and localization for watermarking technique using LSB encryption for DICOM image," *Journal of Discrete Mathematical Sciences and Cryptography*, vol. 25, no. 1, pp. 193–204 (2022).

[28] A. Larxel, "Skin Lesion Images for Melanoma Classification" Kaggle ISIC dataset (2019), [Online]. Available: https://www.kaggle.com/datasets/andrewmvd/isic-2019.

Received April, 2025