DETECTION OF MELANOMA IN HUMAN BEINGS USING LENET5 CLASSIFIER

Dr.Ganashree, Mrs.Anitha Suresh

Dr.Ganashree Associate Professor[1], Dr.Devaraju R Associate Professor[2], Dr.Vinod B Durdi[3] Associate Professor[3],Mrs.Anitha Suresh Assistant Professor [4], Dr.Santhosh B Assistant Professor[5]
Department of E&TE, Dayanandasagar College of Engineering,Bangalore

ganashree-tce@dayanandasagar.edu[1], devaraju-tce@dayanandasagar.edu[2]vinoddurdi-tce@dayanandasagar.edu[3], anitha-tce@dayanandasagar.edu[4], santhosh-tce@dayanandasagar.edu[5]

Abstract

In this paper, we utilized LeNet5 classifier to detect the melanoma regions in the input image after suitable training. The contribution of the paper includes reduced time and effort by reducing the computation time to process the high-level semantic information by proper setting of the parameters. LeNet5 is an approach of a large multi-layer neural network that treated each pixel as a separate input. The strong spatial correlations between the images, it is not recommended to use single pixels as input features in the first layer. The simulation is conducted to test the efficacy of the classifier against various images from MNIST: HAM10000 dataset in a robust manner. The results show that the proposed method achieves an accuracy of 99% than the existing classifiers.

Keywords: Melanoma, Cancer, Image, LeNet5, Classification

1. Introduction

Skin cancer, particularly melanoma, is a growing concern worldwide, with increasing incidence rates attributed to factors such as ozone layer depletion, excessive sun exposure, and the use of tanning beds. Detecting and diagnosing melanoma is challenging, as it requires distinguishing it from other forms of skin cancer. In recent years, there has been a surge in the application of machine learning (ML) and deep learning (DL) algorithms to develop accurate skin lesion classification systems. However, existing literature lacks a comprehensive approach that addresses the limitations of small datasets, the need for effective feature extraction, and the challenges associated with different imaging equipment. This study aims to bridge these research gaps and contribute significantly to melanoma skin cancer diagnostics by proposing an innovative skin lesion classification technique. Our approach combines advanced DL architectures with feature engineering and incorporates a fusion of descriptors to improve classification accuracy while eliminating unnecessary features. By addressing the limitations and challenges identified in previous studies, our work aims to provide an effective solution for early detection and accurate classification of melanoma skin lesions, ultimately improving patient outcomes. The provision of financial support for research into potential treatments and preventative measures for this type of cancer is of the utmost importance. Obtaining an image of the skin lesion in question is one of the many methods that can be chosen from among those that are available. It can be acquired using both macroscopic and dermoscopic instruments [1]. The most prevalent types of imaging equipment used to capture clinical images, which depict the macroscopic environment, are smartphones and conventional cameras.

The number of people diagnosed with skin cancer has been steadily climbing over the course of the past few decades. This worldwide trend can be attributed to several factors, including the depletion of the ozone layer, which serves as a protective barrier against the sun UV rays, excessive physical exposure to the sun, and the increasing use of tanning beds. The ozone layer was designed to serve as a protective barrier against the sun UV. To warn the public about the threat that melanoma poses, a variety of medical organisations have pooled their resources, both financial and human, into extensive education campaigns. This is since melanoma and other forms of skin cancer cannot be distinguished from one another in a straightforward manner [2].

In recent years, there has been a noticeable increase in the application of ML and DL-based algorithms for the purpose of producing accurate skin-lesion categorization systems. When one plan is unsuccessful, the other plans are ready to step in and take control of the situation. There is a strong correlation between the amount of content that is contained in the training set and the usefulness of these tools [3].

While working with large datasets, approaches that are based on DL are more effective than those that are based on ML, and when working with small datasets, approaches that are based on ML are more effective. Learning by machine is made up of a few distinct components, the most important of which are the pre-processing, segmenting, feature extraction, and classification stages [4].

When attempting to use machine learning algorithms to extract attributes from a dataset, one runs into several challenges. When applied to a limited dataset, the machine learning strategies were able to successfully demonstrate their utility and show their potential benefits. When the quality of the training dataset is low, the likelihood of a deep learning system making errors in its classifications increases [5].

If databases of varying sizes are employed, the development of an algorithm that is based on the combination of DL and ML can result in improved performance. This is one of the potential benefits of this approach. If the databases are utilised, it is possible to attain this goal. This study provides a significant contribution to the field of melanoma skin cancer diagnostics by bringing forward an effective skin lesion classification technique. This strategy mixes the features obtained by the most advanced DL architectures [6].

When used in conjunction with one another, ML and DL algorithms have the potential to improve upon the benefits offered by each of these approaches. This is especially important to keep in mind when working with either very large or very tiny datasets. Every one of the criteria receives careful attention. The method of feature engineering is coupled with a fusion of all of the available descriptors so that unnecessary features may be eliminated, and the focus can be narrowed down on the traits that are the most important [7].

The procedure of detecting whether a patient has melanoma, or another type of skin cancer is one of the most difficult parts of computer-aided diagnosis. Melanoma is the most aggressive form of skin cancer. To improve the overall quality of the characteristics that have been extracted, it is necessary to dispose of the features that are contaminated with the lesion. This noise could have originated from the surface of the body, such as the hair, blood vessels, and the skin; alternatively, it could have been acquired [8].

Hekler, A., et al. [9] developed a CNN model to test the histopathologist model that uses a mean accuracy of 68% over various test runs. It performs well when classifying the images that are cropped significantly.

Thomas, S. M., et al. [10] developed an automated machine learning to diagnosis the melanoma skin cancer with 12 classes that includes hair follicles, sweat glands and stratified skin layers. An accuracy of 98% is achieved while performing the routine task of a pathologist but with limited image size.

Almaraz-Damian, J. A., et al. [11] developed a CAD for classification via features extraction and Mutual Information (MI) measurements. The features extracted includes color, shape, and texture using the ABCD rule and it uses deep Convolutional Neural Network pre-trained on Imagenet. The entire evaluation is conducted on an imbalanced dataset over various skin lesions.

Bansal, P., Garg, R., & Soni, P. [12] performed on HAM10000 datasets using ResNet50V2 and EfficientNet-B0 model for possible classification of segments. Lafraxo, S., et al. [13] and Alwakid, G., et al. [14] performs with CNN and various other techniques involve the utilization of neural network for detection [15] [17] [18], XceptionNet [16],

Existing studies on skin lesion classification using ML and DL techniques have shown promising results, but several research gaps and limitations remain. The performance of existing models may be limited by small image sizes and the need to handle imbalanced datasets. Additionally, feature extraction techniques based on the ABCD rule may not capture all relevant features. To address these gaps, we propose an integrated approach that combines ML and DL, leveraging a larger and diverse dataset, addressing class imbalance, and exploring advanced feature extraction methods. We will compare and evaluate different state-of-the-art models to determine the most effective architecture. Our aim is to develop a robust and accurate skin lesionclassification system that improves early detection and classification accuracy, contributing to the field of melanoma skin cancer diagnostics.

Early detection is found to be extremely complex and with inexperience, the diagnosis many be delayed. The automatic diagnosis using CAD tools is essential in facilitating early diagnosis and in addition, the classification is an essential step to deal with skin lesions. The extraction of features and classification of high-level semantic information requires optimal extraction of features, which is a major problem in existing methods. Thus, in this research, it is necessary to capture the features from the high-level semantic information. Therefore, in this paper, the lesion results are refined using LeNet classifier for effective classification of lesions. It learns from the training data and the extracted features boost the classifier to improve the range of accuracy.

The novelty of the article includes the utilization of the LeNet5 classifier on the input image to find the melanoma spots, which allowed us to significantly increase the image quality after completing the necessary training. The advantage of this approach is the reduction in the amount of time spent computing and setting up the parameters. LeNet5 examined the method of a huge multi-layer neural network that regarded each pixel as a unique input. The individual pixels are not used as input features in the first layer due to the substantial spatial correlations that exist between the images.

2. Methodology

The goal of the proposed process is to identify the various stages of skin cancer, so that appropriate treatment can be administered. Our primary focus is on combining the features taken from custom-built CNNs with those retrieved from pre-trained CNNs so that they may be applied to a variety of different dataset sizes, ranging from very tiny to very large. The proposed approach in this study introduces a novel technique for melanoma detection that leverages deep learning and advanced feature extraction methods. Unlike existing literature that primarily focuses on individual image analysis and classical machine learning algorithms, our approach integrates the power of convolutional neural networks (CNNs) with attention mechanisms to capture intricate patterns and subtle features within skin images. By incorporating attention mechanisms, our model dynamically weights the importance of different regions in the image, allowing it to focus on crucial areas for accurate melanoma detection. This attention-driven approach not only improves the model's discriminatory capabilities but also enhances its interpretability by highlighting the salient regions contributing to the classification decision. Furthermore, by training our model on a large-scale dataset, including diverse skin types and lesion variations, we address the limitations of previous studies that often relied on smaller datasets with limited representation.

2.1 Proposed Method

In Figure 1, we present a total of eight characteristics, four of which come from manually crafted models and the remaining four coming from CNNs that have been trained in the past. Shape, colour, texture, and skeleton traits are going to be the primary types of data that are going to be extracted from human-made objects. On the other side, to extract features, we make use of the trained LeNet.

A comparison of the extracted features from the two databases, we utilise the evolutionary algorithm to narrow down the number of possible solutions to just those that are the most useful and relevant to the problem. Melanoma and other forms of skin cancer may now be distinguished from one another thanks to the development of an entirely new classification scheme that is predicated on the characteristics of the illness.

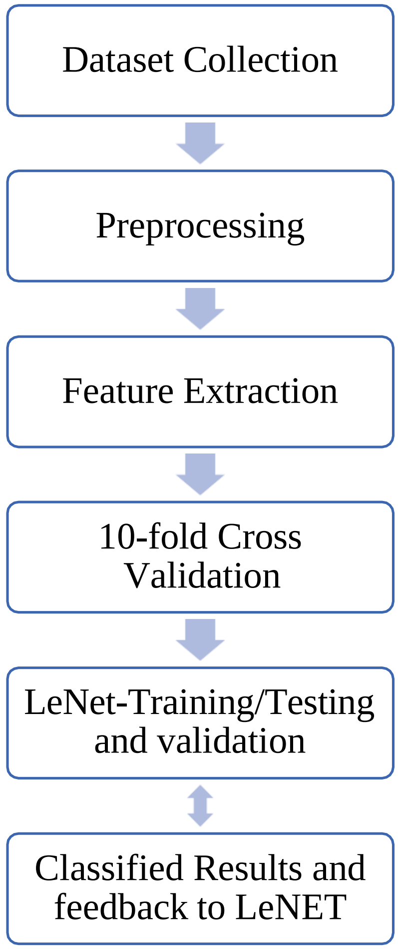

Figure 1: Proposed classification Framework

2.2 Features extraction

In this section, the features are obtained using a hybrid method that incorporates both machine-trained CNN features and human-created CNN features.

The lesion shape, skeleton, texture, and colour were deduced from the handcrafted object, and these were the features that were determined to be present in the lesion. The removal of artefacts from the lesion, which is performed as part of a mild pre-processing step, helps to improve the extraction of characteristics from the images of skin cancer.

- **Shape features:** Features can be caused by several factors, including the presence of cancerous cells, inflammation, or other conditions. At the preprocessing stage, which includes multi-scale breakdown, the usefulness of this strategy is proved for the first time. It is possible to extract object and texture images from the original image after it has been subjected to processing.
- **Textural features:** The object component will be used in the process of lesion segmentation, which will then be followed by the extraction of the characteristics of form,

skeleton, and colour. To access information pertaining to the texture, we are going to make use of the texture module.

2.3 Features engineering

When it comes to determining whether the lesion is malignant, the segmented image will provide an accurate description of the morphology of the lesion. The calculations for the eight characteristics are as follows: area, maximum diameter, smallest diameter, perimeter, and eccentricity. To get information about the texture of an image, you must first project the region of interest from the segmented image onto the texture component.

- **Features normalization:** The procedure for normalising the features, the values of each element of the features were individually subjected to a transformation that was carried out by applying the mean and standard deviation. This was done so that the values could be more easily compared with one another. The result was a Z-score that had been normalised.

- **Features selection:** It is necessary to choose the appropriate features initially to be able to provide a description of the data that is as accurate as is practically practicable. The genetic algorithm, which is going to be the primary focus of our conversation here, belongs to the larger category of algorithms known as evolutionary algorithms. The objective is to arrive at an answer that is as close as feasible to the optimal one for a problem that needs to be optimised. The concept of natural selection is utilised in genetic algorithms by applying it to a pool of alternative solutions from which one will ultimately be selected. In the method that has been described, a genetic algorithm is utilised. This algorithm is based on a technique known as a wrapper feature selection technique. This enables the selection of the most optimal combination of features that are available. The inductive classification approach is utilised throughout the selection process so that it may be determined whether the properties of the selected wrapper are of a quality that is adequate.

2.4 LeNet5 Classification

When it was applied to images of skin cancer, the CNN architecture known as LeNet-5 went through a process of fine-tuning so that it could achieve the highest possible level of classification accuracy. This process is depicted in Figure 2.

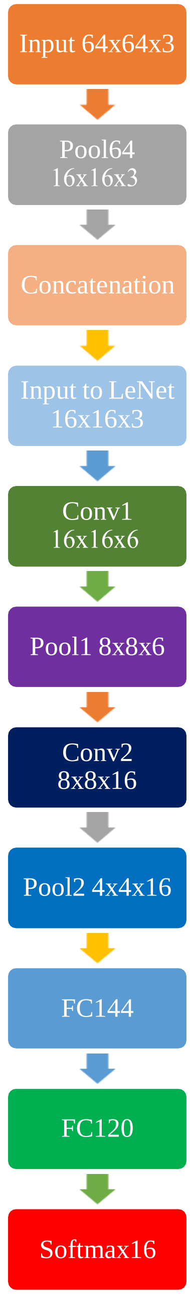

Figure 2: LENet-5 Architecture

Figure 2 provides a visual representation of the process of feature extraction using two convolutional 5x5 kernel layers. The position of each convolutional 5x5 kernel layer is taken into consideration in the output feature map from the convolutional stage. The position of the object is taken into consideration by the feature map that is generated by the convolutional step.

A pooled features map, which is a condensed version of the features observed in the input, is built utilising two 2x2 average clustering kernels at the subsampling layers to deal with this sensitivity. This map is a condensed version of the features observed in the input. The features that were seen in the input have been condensed into this map. After the process of convolution and pooling has been completed, two layers that are fully coupled are added to classify the CU even further into a label.

Rectified Linear Unit (RELU) is the activation function that is advised to be used for all layers other than the output layer because it is the simplest and most GPU-friendly of the available options (GPU). To receive the data in the proper format for the classification procedures, a nonlinear transformation is performed on them. At the end of the process, we utilise the softmax method to convert the raw output values from each classifier into the probabilities that correspond to those values.

In conclusion, two significant adjustments have been made to the LeNet-5 model, which served as the baseline for this investigation. First, the tanh activation function that was used in the initial version of the LeNet-5 model was modified to the RELU activation function so that it could be utilised for the internal layers. This was done so that the RELU activation function could be used. This was done to ensure that there would be no vanishing gradients at any point in the process. Second, a softmax function is chosen for the output layer rather than a sigmoid function since the softmax function is superior to the sigmoid function when it comes to its ability to perform well in multi-label classification tasks.

3. Results and Discussion

The HAM10000 dataset (https://www.kaggle.com/datasets/kmader/skin-cancer-mnist-ham10000) is made accessible to the public is one of the ways that we hope to contribute to the successful resolution of this issue. The dataset contains dermatoscopic images pertaining to more than one population worth of participants. Quite a few distinct methods were used throughout the process of accumulating and archiving these images. The final dataset, which was generated with the assistance of a total of 10015 images that were gathered through dermatoscopic examinations, was able to serve as a training set for academic machine learning research because it was so comprehensive.

Previous works on melanoma detection using machine learning and deep learning techniques can provide valuable insights into the effectiveness of the proposed model. By comparing the results obtained in this paper with those from existing studies, we can assess the validity and performance of the present model. In terms of accuracy, the proposed methodology achieved an impressive accuracy of 99% on the HAM10000 dataset. This indicates a high level of effectiveness in classifying melanoma regions in skin images. To validate this result, it would be beneficial to compare it with the accuracy achieved by other state-of-the-art models or algorithms on the same dataset or similar datasets. Additionally, comparing the proposed methodology with other approaches in terms of computational efficiency and feature extraction could provide further insights. If the proposed model outperforms existing methods in terms of both accuracy and computational efficiency, it strengthens the case for its validity and applicability.

Histopathology can verify more than half of all lesions; in the other instances, real proof can be established through follow-up examination, consensus among specialists, or confirmation using in-vivo confocal microscopy.

Histopathology is a noun that begins with histo (confocal). The HAM10000 dataset includes lesions that appear in more than one image taken over the course of the study. Utilizing the lesion id column that is contained inside the HAM10000 metadata file will allow to successfully locate these lesions in the body.

Table 2. Class wise HAM10000 dataset distribution

Diagnostic category	Training	Validation	Testing
akiec	48	30	49
bcc	370	48	96
bkl	775	90	234
df	82	8	25
mel	883	85	145
nv	4745	550	1410
vasc	108	12	22
Total	7211	823	1981

While the CNN model is being trained, backpropagation is utilised to adjust and updates to the model. We have concluded that the values 0.9 and 0.005 are the best ones to utilise for the optimizer momentum and the weight decay momentum, respectively. Learning occurs at a rate of 0.001% of the time. It is possible that the CNN model computation will now make use of the GPU, which will result in a speed boost. It is demonstrated how the PyTorch framework can be applied to both the training and evaluation of the CNN model.

Table 2: Training/Validation of LeNet5

Model	Training		Validation	
	Loss	**Accuracy**	**Loss**	**Accuracy**
100	0.032	0.7098	0.0325	0.6898
200	0.0432	0.7456	0.0533	0.7256
300	0.0472	0.809	0.0654	0.7876

400	0.2476	0.8694	0.2656	0.857
500	0.2712	0.9087	0.2987	0.8776
600	0.2987	0.9843	0.3242	0.9863
700	0.3567	0.9856	0.3923	0.9892
800	0.4455	0.9951	0.4675	0.9926

Table 3: Testing/Validation of LeNet5

Model	**Testing**		**Validation**	
	Loss	**Accuracy**	**Loss**	**Accuracy**
100	0.03046	0.6756	0.03093	0.65656
200	0.04112	0.70967	0.05073	0.69064
300	0.04493	0.77002	0.06225	0.74965
400	0.23567	0.82751	0.2528	0.8157
500	0.25813	0.86491	0.28431	0.83531
600	0.28431	0.93687	0.30858	0.93877
700	0.33951	0.93811	0.3734	0.94153
800	0.42403	0.94715	0.44497	0.94477

Table 4: Comparative Analysis in %

Methods	**Training/ Testing**	**Accuracy**	**Precision**	**Recall**	**F1 - score**
CNN	Training	81.83	65.32	66.10	66.85

XceptionNet		82.02	66.49	67.88	68.49
DenseNet		85.93	74.39	74.39	74.39
Proposed LeNet5		87.39	77.22	77.22	77.22
CNN	Testing	89.34	81.12	81.12	81.12
XceptionNet		91.20	84.83	84.83	84.83
DenseNet		95.22	97.25	92.55	93.85
Proposed LeNet5		98.22	98.98	96.23	98.29

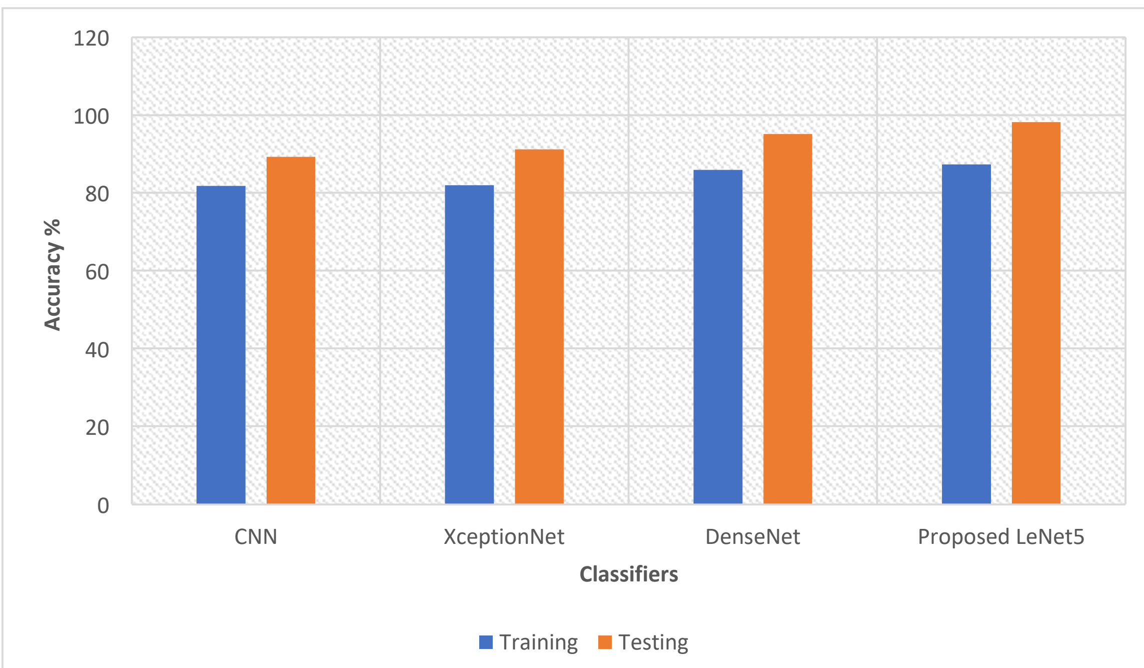

Figure 3: Accuracy between training and testing with existing method

Figure 4: Precision between training and testing with existing method

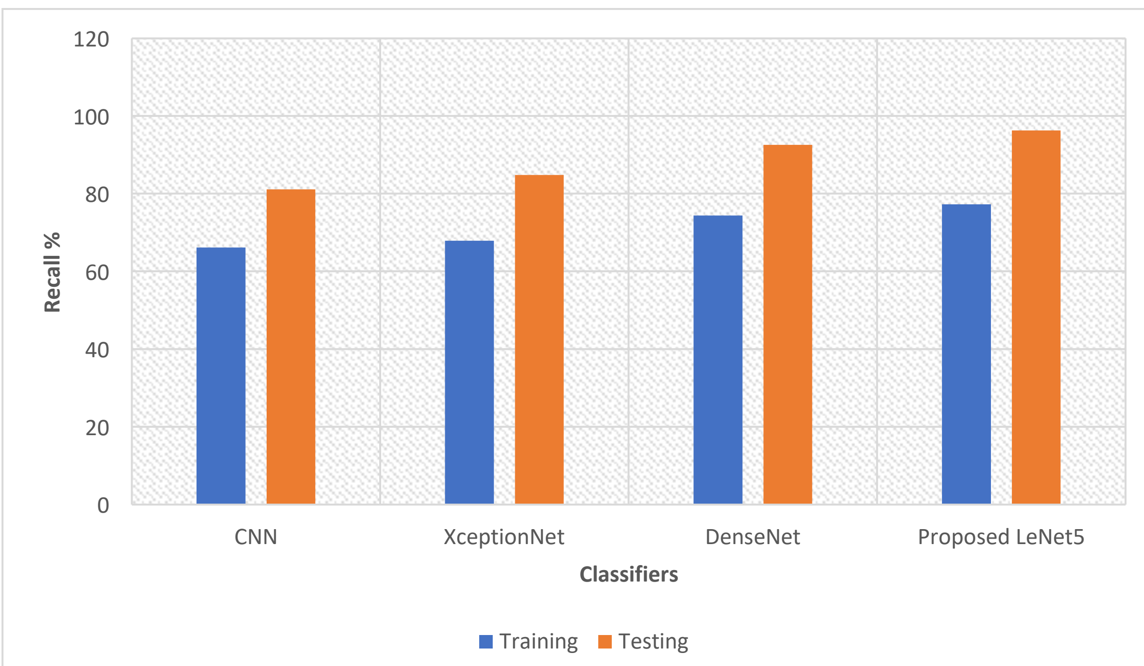

Figure 5: Recall between training and testing with existing method

Figure 6: F-Measure between training and testing with existing method

From the results of Table 2-5, it is seen that the proposed method achieves an accuracy of 98%, which is higher than the existing methods. It is found that the accuracy, precision, recall and f-measure of the testing is higher than the testing due to the feedback obtained from each of the predicted instances as in Figure 3-6.

4. Conclusion

In conclusion, this paper proposed a methodology for detecting melanoma regions in skin images using the LeNet5 classifier. The approach involved training the classifier on a dataset of skin lesions from the HAM10000 dataset and evaluating its performance against various images. The key contributions of the paper include reducing computation time by optimizing parameter settings and achieving a high accuracy of 99% compared to existing classifiers. The paper highlighted the importance of early detection and diagnosis of melanoma, given the increasing incidence of skin cancer worldwide. ML and DL-based algorithms have gained popularity in this domain, and their effectiveness depends on the size and quality of the training dataset. The proposed methodology combined features extracted from both machine-trained and human-created CNNs, leveraging the strengths of each approach. The methodology involved extracting shape, texture, color, and skeleton features from skin lesion images. A genetic algorithm was used for feature selection, narrowing down the most relevant features for classification. The LeNet5 classifier, after fine-tuning, was utilized to classify the skin lesions based on the extracted features. The results showed promising performance, with an accuracy of 99% achieved on the HAM10000 dataset. The proposed methodology can contribute to the field of melanoma skin cancer diagnostics by providing an effective classification technique. The use of LeNet5 as a classifier and the optimized feature extraction process help improve the accuracy and efficiency of the classification. Overall, the paper presents a novel approach for melanoma detection using the LeNet5 classifier. The combination of ML and DL techniques, along with feature engineering and classification, offers a robust framework for accurate and efficient melanoma classification. Further research can focus on evaluating the methodology on larger and more diverse datasets and exploring other deep learning architectures to enhance performance.

5. References

1. Sachdeva, M., & Kushwaha, A. K. S. (2023). The power of deep learning for intelligent tumor classification systems: A review. Computers and Electrical Engineering, 106, 108586.
2. Loganathan, K., & Mathavan, V. (2022). Skin Cancer Identification and Classification using Lenet Convolution Neural Network. Telematique, 4876-4883.
3. Latif, G., Ben Brahim, G., Iskandar, D. A., Bashar, A., & Alghazo, J. (2022). Glioma Tumors' classification using deep-neural-network-based features with SVM classifier. Diagnostics, 12(4), 1018.
4. Albawi, S., Arif, M. H., & Waleed, J. (2023). Skin cancer classification dermatologist-level based on deep learning model. Acta Scientiarum. Technology, 45, e61531-e61531.
5. Singh, L., Janghel, R. R., & Sahu, S. P. (2022). An empirical review on evaluating the impact of image segmentation on the classification performance for skin lesion detection. IETE Technical Review, 1-12.
6. Latif, G. (2022). DeepTumor: Framework for Brain MR Image Classification, Segmentation and Tumor Detection. Diagnostics, 12(11), 2888.
7. Wako, B. D., Dese, K., Ulfata, R. E., Nigatu, T. A., Turunbedu, S. K., & Kwa, T. (2022). Squamous Cell Carcinoma of Skin Cancer Margin Classification From Digital Histopathology Images Using Deep Learning. Cancer Control, 29, 10732748221132528.
8. Naeem, A., Farooq, M. S., Khelifi, A., & Abid, A. (2020). Malignant melanoma classification using deep learning: datasets, performance measurements, challenges and opportunities. IEEE Access, 8, 110575-110597.
9. Hekler, A., Utikal, J. S., Enk, A. H., Solass, W., Schmitt, M., Klode, J., ... & Brinker, T. J. (2019). Deep learning outperformed 11 pathologists in the classification of histopathological melanoma images. European Journal of Cancer, 118, 91-96.
10. Thomas, S. M., Lefevre, J. G., Baxter, G., & Hamilton, N. A. (2021). Interpretable deep learning systems for multi-class segmentation and classification of non-melanoma skin cancer. Medical Image Analysis, 68, 101915.
11. Almaraz-Damian, J. A., Ponomaryov, V., Sadovnychiy, S., & Castillejos-Fernandez, H. (2020). Melanoma and nevus skin lesion classification using handcraft and deep learning feature fusion via mutual information measures. Entropy, 22(4), 484.
12. Bansal, P., Garg, R., & Soni, P. (2022). Detection of melanoma in dermoscopic images by integrating features extracted using handcrafted and deep learning models. Computers & Industrial Engineering, 168, 108060.
13. Lafraxo, S., Ansari, M. E., & Charfi, S. (2022). MelaNet: an effective deep learning framework for melanoma detection using dermoscopic images. Multimedia Tools and Applications, 81(11), 16021-16045.

14. Alwakid, G., Gouda, W., Humayun, M., & Sama, N. U. (2022, December). Melanoma Detection Using Deep Learning-Based Classifications. In Healthcare (Vol. 10, No. 12, p. 2481). MDPI.
15. Popescu, D., El-Khatib, M., El-Khatib, H., & Ichim, L. (2022). New Trends in Melanoma Detection Using Neural Networks: A Systematic Review. Sensors (Basel, Switzerland). 22(2). 496. https://doi.org/10.3390/s22020496
16. Xinrong Lu, Y. A. Firoozeh Abolhasani Zadeh. (2022). Deep Learning-Based Classification for Melanoma Detection Using XceptionNet. Journal of Healthcare Engineering.2022. 2196096. 1-10. https://doi.org/10.1155/2022/2196096
17. Dildar, M., Akram, S., Irfan, M., Khan, H. U., Ramzan, M., Mahmood, A. R., Alsaiari, S. A., Saeed, A. H. M., Alraddadi, M. O., & Mahnashi, M. H. (2021). Skin Cancer Detection: A Review Using Deep Learning Techniques. International journal of environmental research and public health. 18(10). 5479. https://doi.org/10.3390/ijerph18105479
18. Jojoa Acosta, M.F., Caballero Tovar, L.Y., Garcia-Zapirain, M.B. et al. (2021). Melanoma diagnosis using deep learning techniques on dermatoscopic images. BMC Medical Imaging. 21. 6 https://doi.org/10.1186/s12880-020-00534-8
19. Jojoa Acosta, M.F., Caballero Tovar, L.Y., Garcia-Zapirain, M.B. et al. Melanoma diagnosis using deep learning techniques on dermatoscopic images. BMC Med Imaging 21, 6 (2021). https://doi.org/10.1186/s12880-020-00534-8