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A machine learning model for skin disease classification using convolution neural network

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Abstract
Melanoma is a skin disease that tends to be lethal. It occurs when melanocytes develop in an uncontrolled manner. Melanoma goes under a few different names, including malignant melanoma. The incidence of melanoma is at its highest level ever recorded in both Australia and New Zealand. It is estimated that one in every 15 white New Zealanders will indeed be diagnosed with melanoma at some point in their lives. Aggressive malignancy was the third most common kind of cancer in men and women in 2012, respectively. Melanoma can develop at any age in adults, but it is highly unusual in children and teenagers. It is hypothesized that the first step in developing melanoma is an unregulated multiplication of melanocytic stem cells that have been genetically altered. The survival rate can significantly increase if melanoma is identified in dermos copy images at an earlier stage. On the other hand, the detection of melanomas is an incredibly challenging task. Consequently, the detection and recognition of skin cancer are of tremendous assistance to the accuracy of pathologists. In this research, a deep learning technique is shown for reliably diagnosing the type of melanoma present at a preliminary phase. The proposed model makes a distinction among lesion maligna, superficial spreading, and nodular melanoma. This permits the early diagnosis of the virus and the quick isolation and therapy necessary to stop the transmission of infection further. Deep learning (DL) and the standard non-parametric machine learning method are exemplified in the deep layer topologies of the convolutional neural network (CNN), which are neural network algorithms. The effectiveness of a CNN classifier was evaluated using data retrieved from the website https://dermnetnz.org/. The outcomes of the experiments show that the proposed method is superior in terms of diagnostic accuracy compared to the methodologies that are currently considered state of the art.

Keywords: Types of melanoma, skin disease, deep learning models, convolutional neural network, machine learning classification

1. Introduction

Since the 1970s, skin cancer has held the title of the most prevalent disease globally. Over the previous several decades, there has been an uptick in people diagnosed with non-melanoma and melanoma skin cancers, respectively. Melanoma can be identified in that only one in three cases of cancer, as stated by the World Health Organization (WHO), and according to statistics provided by the Skin Cancer Foundation, one out of every five people in the United States will develop skin cancer at some point during their lifetime. For the past several centuries, the incidence of skin cancer has risen at a relatively constant rate, particularly in the Western hemisphere. Countries such as the United States, Canada, and Australia are just some of the places where this trend has been observed. Infectious diseases of the skin typically have the potential to have a significant detrimental effect on the overall health of people all over the world. According to one piece of a study released in 2017, multiple studies have demonstrated that skin cancer is responsible for 1.79 percent of the disease burden assessed in disability-adjusted life years on a global scale [1]. The incidence of skin cancer accounts for around 7 percent of all newly diagnosed instances of cancer worldwide [2], resulting in a loss of more than $8 billion for the Medicare program in the United States in 2011. Clinical data suggest that there are such disparities in results based on race in the case of skin cancer: Even though people with darker skin tones are approximately 20 to 30 times as likely to develop melanoma than those who have lighter skin tones, it has been discovered that people with darker skin tones either have a higher or lower mortality risk for specific types of melanoma, depending on their skin tone.

In order to administer the appropriate treatment, it is essential to identify a skin lesion correctly. It is possible to accomplish early diagnosis of melanoma in dermoscopy photographs and pictures using this method, which improves the survival rate.

Dermatologists who have had considerable training in the many skin lesions that melanomas might cause are the most qualified to make an accurate diagnosis. Because of this, diagnosing melanoma can be a challenging task because there is no clear separation between skin lesions and the skin itself, malignant and non-melanoma skin lesions appear visually similar, and there are other factors to take into account. Therefore, creating a trustworthy automatic detection method for skin tumors, such as a system that can automatically analyze skin lesions, will be greatly useful to pathologists. This is especially relevant in an era where knowledge is scarce.

According to the findings of this study, the classification methods of K-nearest Neighbors, Support Vector Machines, and Decision Trees all produced subpar results in terms of precision and accuracy. After conducting further research into the mathematics that underlies classification, it was found that employing Deep Learning models was the most sophisticated method for getting the desired outcomes (also known as deep learning models). We experimented with many different mathematical models, both with and without the application of Learning Algorithms. However, we concluded that the depth and quality of activation that was made available by pre-trained models did not meet up. Consequently, we merged our mathematical expertise and developed a model known as a Dense Convolutional Network, which offered an accuracy of more than 86.6 percent.

We were able to accomplish efficient and reliable picture categorization by using Deep Learning, a branch of artificial intelligence that is exceptionally robust and potent in its capabilities. The structure and operation of this artificial brain were extremely comparable to those of the human brain, with neurons activating across the brain to transfer information, categorize the data, draw conclusions, and produce consequences. Neural Networks are used in Deep Learning, a form of machine learning. A Neural Network structure is a stack of layers collectively known as a Neural Network structure. As their name suggests, neural networks can perform functions comparable to those that neurons in the brain can execute, such as recognizing patterns and generating predictions.

The project's overarching objective is to come up with a method of screening for skin cancer that is both reasonably quick and straightforward for the general public to use. In most instances, the sooner it is recognized, the better the probability that the individual will make a full recovery. According to the American Academy of Dermatology Association, most dermatological malignancies are treatable if found at an early stage. The trained model is just a preliminary step before doing a skin biopsy. Visit a dermatologist and get a skin biopsy performed if you want to know for sure if you have skin cancer or not. This is the only method to get an accurate diagnosis.

The organization of this document is broken down into its parts in the following paragraphs. In Chapter 2, "Literature Survey," there was a comprehensive summary of all the previous studies. In Section 3, you should describe the design of the proposed system (System Architecture). The experimental setup and the dataset used in the experiment are discussed in Section 4 (Results and Discussion). Section 4 also examines the results of the experiment. Finally, in the section under "Conclusion," both the conclusion reached about the system and the work that will be done in the future to improve it were discussed.

2. Literature Survey

In order to address the major three aims in the field of skin lesion image processing, the author of this study [7] utilised two different deep learning algorithms, namely the Lesion Feature Network (LFN) and the Lesion Indexing Network (LIN). a) The division of the lesions into segments b) The Removal of Dermoscopic Characteristics from the Lesion c) The Categorization of the Lesion The author suggests a deep learning system that is made up of two fully convolutional residual networks (FCRN), which produce results for segmentation and classification. In order to refine the findings of the coarse classification, the lesion index calculation unit (LICU) is constructed by employing a distance heat map. A straightforward CNN is demonstrated as a solution to the problem of extracting dermoscopic features. In order to assess the provided deep learning framework, the author employed the ISIC 2017 dataset. The author's experiment shows that the suggested (LIN) performs better than existing machine learning algorithms for lesion segmentation and classification. However, for dermoscopic feature extraction, the performs better than the proposed (LIN).

The author developed a fully automatic method for the segmentation of skin lesions in the article [8]. This method makes optimal use of a trained 19-layer deep CNNs and therefore does not rely on prior knowledge of the data. The author came up with a series of strategies to assure effective and efficient learning despite having very little training data to work with. When using cross entropy as the loss function for picture segmentation, which is a normal process, there is a severe imbalance between both the amount of foreground and background pixels. As a result of this, an original loss function based on Jaccard distance has also been designed to minimise the requirement for sample re-weighting. The author made use of two datasets that are open to the public in order to evaluate the usefulness, efficiency, and potential for generalisation of the proposed framework. These databases are the ISBI 2016 database and the PH2 database.

The authors of [9] show how to identify skin lesions using a single CNN that was trained from the ground up using photographs utilising only pixels and sickness labels as inputs. This method was used to train the CNN from start to finish. In order to train CNN, the author employed a dataset consisting of 129,450 clinical photos, which is two orders of magnitude greater than the prior datasets, which consisted of 2,032 disorders. Utilizing biopsy-proven clinical pictures, 21 board-certified dermatologists evaluate the performance of the system in two binary classification use cases: keratinocyte carcinomas versus benign seborrheic keratoses and malignant melanomas versus benign nevi. Both use cases compare the system's accuracy in diagnosing the two types of skin lesions. In the first situation, it is necessary to determine which malignancies are the most prevalent, and in the second scenario, it is necessary to determine which skin cancer is the deadliest. According to the results of the author's experiment, CNN performed better than all of the specialists who were tested in both tasks, proving that machine learning is capable of recognizing skin cancer at a level of competence comparable to that of dermatologists.

The author of this article [10] presents a novel method for melanoma recognition that is based on deep CNNs and contrasts it to earlier methods that were either based on low-level hand-crafted features or CNNs with shallower architectural designs. According to the authors' findings, their method, which makes use of substantially deeper networks, is able to learn discriminative traits, which results in better identification accuracy. In order to make full use of very deep networks, the author proposed a variety of methodologies that can be used to ensure good training and learning even with a limited amount of training data. The following procedures make up the method: a) When a network goes deeper, employ residual learning to address degradation and overfitting issues so that the network may continue to function properly. The performance gains that were made possible by raising the network depth will be preserved as a result of this action. b) Construct a fully convolutional residual network (FCRN) for accurate skin lesion segmentation, and then enhance it through the application of a multi-scale contextual information integration technique. c) If you want to make a two-stage framework, combine the deep residual networks and the FCRN that was provided. This approach enables the classification network to extract more representative and specific features from segmented findings rather of the complete dermoscopy images, hence reducing the quantity of training data that is required to be collected. The author used the ISBI 2016 dataset for the purpose of evaluation.

Rashmi Patil and her associates [11] with the gradient descent Similarity Measure presented CNN approach for Text Processing (SMTP). This research resulted in the development of two different methods for identifying the stages of melanoma cancer. In the first approach, melanoma is divided into two phases, which are referred to as stages 1 and 2. Melanoma is divided into three distinct phases, which are referred to as stages 1, 2, and 3. The suggested SMTP loss function causes exceptionally little loss in compared to all of the previous loss functions, and this has shown to be very effective in terms of enhancing sensitivity, specificity, and accuracy.

Konstantin Korotkov and colleagues [12] described approaches to address the issue of matching skin lesions as part of their research. The process known as "whole body photography" entails taking clinical photographs of patients in various seated positions while they are in an institutional setting. Clinical specialists in total body skin evaluation make use of photographs in order to document the current condition of a patient's skin, as well as study the progression of a variety of cutaneous conditions. It plays an important role in the early detection of melanoma, a potentially fatal form of skin cancer. Images of skin lesions are shown by circles that are a perfect fit within optimally steady extreme areas. After the lesion has been identified, those results will be added to the matching algorithm.

M. A. Kassem and colleagues introduced a method that makes use of transference learning and a pre-trained Google Network. This method was created for the ISIC 2019 Challenges Data Set. Even if there are imbalances between the classes, the suggested method is still capable of accurately classifying all eight different types of lesions. The suggested methodologies' precision, sensitivity, specificities, and precision were measured, and their respective values were 94.92 percent, 79.8 percent, 97 percent, and 80.36 percent, respectively. The performance of the method that was provided increased when the number of images in each class was decreased in order to eliminate the problem of imbalance between classes. When weight is modified for each layer of the architecture, the performing metrics are significantly higher than those for merely the finished layers. Only the layers that were removed and restored are complete. According to an alternative model, unknown photos could be identified using GoogleNet and SVM multi-class systems. The authors attempted to use the VGG19 in the same way as they used GoogleNet, but they were unable to test the same equipment or use it themselves. It requires very stringent hardware criteria, which most researchers working in different nations simply are unable to meet.

They developed a melanoma detection and segmentation approach in a work that was published by Saleh Albahli and colleagues. [Citation needed] Using morphological procedures on dermoscopic photos allows for the removal of artefacts like hairs, gel bubbles, and clinical marks, as well as the sharpening of image regions. They used the YOLOv4 object detector, which was modified for melanoma detection, to differentiate between strongly correlated infected regions and non-infected regions in order to discover infected regions. Using the ISIC2018 and ISIC2016 datasets, the results of the presented system are analysed and compared to the results of melanoma identification and segmentation techniques.

This model includes a feature discriminating network and a lesion classification network, according to Lisheng Wei *et al.* Additionally, it incorporates a lightweight skin malignant recognition model with feature discrimination dependent on fine-grained classification standard. They devised a discriminating model in order to recognise lesions in dermoscopy images. In order to develop a dermoscopy image lesion classification branch network, it makes use of a pre-trained lightweight network for the purpose of feature extraction. Through collaborative training of each branch network, the presented model is able to conduct simultaneous classification of lesion type and similarity of lesion features. This enables the model to extract more discriminative lesion features. Our framework produces model performance comparable to, and in some circumstances better than, the existing multi-CNN fusion approach or the scheme based on local depth feature Fisher Vector coding, but having fewer model parameters. Our framework's fewer parameters enable this.

Loretta Ichim and her colleagues proposed a unique approach that is built on several neural networks that are connected on two classification stages. Transferring the system's data from one database to another is made easier by using this procedure. The use of several classifiers was suggested as a method that might effectively identify melanomas in images of lesions at a reduced cost. When selecting classifiers, the following considerations were taken into account:

a) Classifiers are to be arranged on two levels of hierarchy, one of which is subjective and the other of which is objective.
b) Classifiers for the first stage that make use of a variety of lesion characteristics.
c) Relevant learning found that any classification dependent on characteristics was subjective.

In addition to this, the implementation of a conditional GAN for categorising accidents in accordance with the ABCD law was an important addition to this. The accuracy of the classifier has been brought up to par. The final classifier was connected with a likelihood that was derived from the TDS score after it had been turned into a probability. The suggested two-tier architecture had the advantage of allowing for quicker switching between databases (or devices), with the need to learn only the second stage (final perceptron PF). The proposedsystem increases the effectiveness of the many alternative comparison approaches. As a consequence of this, the goal neural network achieves a score of 97.5 percent ACC and 94.47 percent, 97 percent ACC, and 93.67 percent F1 correspondingly.

A customised CNN that has the capability to automatically learn features and predict the class of numbers from a big data collection is demonstrated, as well as a visualisation of the intermediate results.

According to D. T. Mane *et al*., customised CNN layers that show the dynamics of the network were developed. There are 80,000 different Marathi numerals; however, only 70,000 are used for instruction, while the remaining 10,000 are put to use in examinations. When the CNN's performance was checked using K-fold cross validation, it attained an accuracy rate of 94.93 percent on average for the data sets that were used for testing. The photos can have high-level properties extracted from them using CNN that has been customised. By combining the capabilities of the central processing unit (CPU) and the graphics processing unit (GPU). The overall accuracy of the system can be summed up as 94.93 percent if we look at it in its whole.

Rashmi Patil *et al*. state that melanomas can manifest in a variety of different ways and might not display any of the typical warning signs. [Citation needed] It is extremely important to detect melanomas in their early stages. This research uses transfer learning to create a computer-aided melanoma assessment tool. Several existing frameworks show that computer vision may be used to find medical images. This paper also describes a computer-aided melanoma identification method. The model correctly categorised lentigo maligna, nodular, and superficial spreading melanoma. Additionally, the model correctly identified uneven borders from melanoma skin lesions, which is an extremely significant finding. A dataset consisting of 2475 dermoscopic images was developed so that algorithms could be trained on and evaluated using the data. Regarding the precision, the f1 score, the recall, and the accuracy. The results of many experiments indicate that VGG19 performs better than ResNet50, VGG16, and MobileNet.

A feed-forward artificial neural network having one or more layers that are entirely coupled together is known as an MLP network. At a minimum, an MLP network will include three layers, which are referred to as "the input layer," "the hidden layer," and "the output layer".

3. Implementation Details

A. Convolutional Neural Network (CNN)

In Image Processing, the most commonly used and efficient algorithm of Deep Learning is CNN. These are the most cutting-edge approaches to deep learning [2]. Due to its parameter-sharing and stronger adaptation capabilities than a deep learning model, CNN has several applications; include biological text analysis, object detection and recognition, and malware classification. Researchers exploit CNN's features in several ways. CNNs were inspired by the cortical organisation for animal vision, which detects light in small patches that overlap one another across the visual field. As we delve deeper into the network, the layers will extract higher-level properties that are increasingly accurate. It is common knowledge that CNN models have the ability to create a correlation between the internal representation of pixel values and how those values are shown in the form of a two-dimensional matrix. It works particularly effectively with information that can be linked to a specific location. The architecture of the CNN is shown in figure 2.

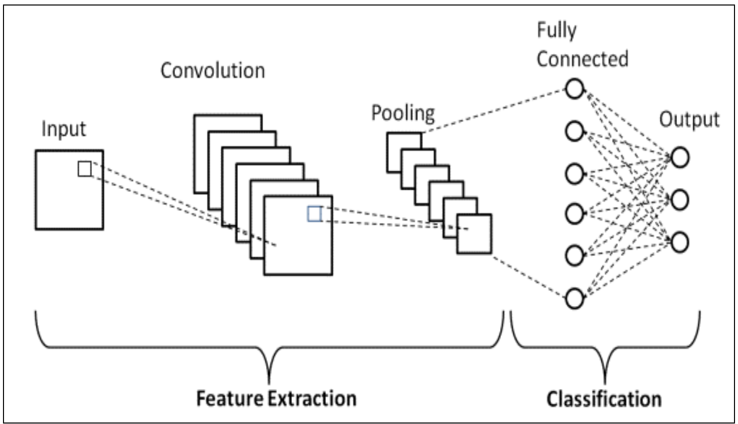

Fig 1: CNN architecture

B. System Architecture

The following are the stages that must be completed in order for our suggested system to be implemented.

1. As input, the system will take a dataset of picture data.
2. To increase the quality of the image and eliminate hairs from it, which was before is carried out before to printing.
3. A training file is formed as a consequence of the extraction of a number of features from the input image dataset.
4. In this experiment, the CNN classification approach is applied to both the newly constructed training file collection and the freshly created test input images, which were both made from scratch.
5. Melanomas are detected by using the CNN algorithm, which determines whether or not melanoma is present in the input test data set.

Finally, in order to determine the overall performances of the proposed technique and provide recommendations, a graphic evaluation is carried out at the conclusion

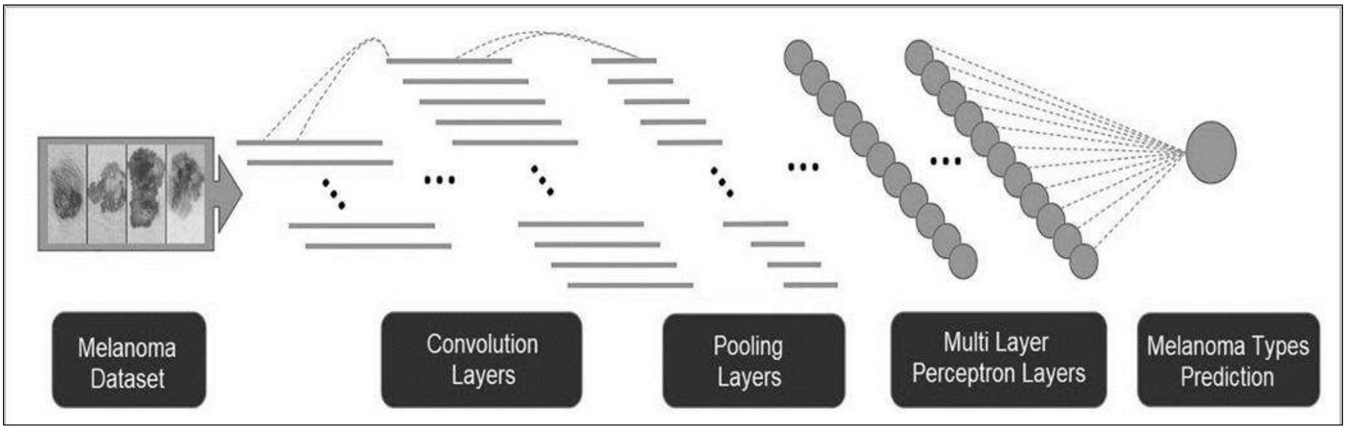

Fig 2: Proposed system architecture

4. Experimental Results

A. Experimental Dataset

The dataset was contributed via the website https://dermnetnz.org/. In order to prevent ourselves from over fitting the data, we made use of a data augmentation method. It's a method for generating new training data artificially out of existing data, using the old data. The photographs have had a zoom effect added to them as an enhancement. It does so in a haphazard manner, either randomly zooming in on the image and adding new image pixels or interpolating existing ones.

Table 1: Dataset Description

Type	Number of Images
Superficial spreading melanoma	936
Nodular melanoma	756
Lentigo maligna melanoma	783

B. Experimental Setup

The research was conducted on a personal computer running Windows 10 that had a Core i7 processor, 8 gigabytes of dynamic random access memory (DDRAM), a GeForce MX150 NVIDIA graphics card, and a 500 gigabyte solid state drive. The Anaconda IDE was utilised so that a programme could be executed.

C. Evaluation Parameters

After the models had been trained, we put them through their paces using the held-over test set. After that, the confusion matrix was utilised in the computation of the performance metrics. In order to signal both intended and actual classifications, elements of the confusion matrix are utilised. The process of classification results in two classes: correct and incorrect. In order to calculate the prediction model, we conducted an analysis of the following four fundamental case studies:

- The term "true positive" refers to the percentage of true positives that are identified with high degree of precision (TP).
- Incorrect forecasts are referred to as having a false negative (FN). It finds situations that are malevolent, despite the fact that the model incorrectly anticipated them to be normal.
- A false positive, sometimes known as an FP, is an incorrectly positive prediction made when the observed assault is, in fact, normal.
- The percentage of false positives that correctly identify attacks is the value that is being measured by the true negative (TN).

When evaluating the performance of suggested task, accuracy, recall, f1 score, and precision are all taken into consideration. The origin of measurements is found in

$$Accuracy = \frac{T_p + T_n}{T_p + T_n + F_p + F_n} \quad (1)$$

$$Precision = \frac{T_p}{T_p + F_p} \quad (2)$$

$$Recall = \frac{T_p}{T_p + T_n} \quad (3)$$

$$F1 = 2X \frac{Precision \ x \ Recall}{Precision + Recall} \quad (4)$$

D. Results Analysis

Table 2: Performance Analysis of ML, and DL Algorithms

Classifier	Precision	Recall	F1-Score	Accuracy
DT	70.00	69.00	59.00	67.00
RF	71.00	71.00	65.00	71.35
GBT	68.00	73.00	70.00	73.44
CNN	91.07	87.68	89.32	88.83

The accuracy graphs with regard to the number of epochs are displayed in Figure 3, which is a comparison of the CNN accuracy and the CNN validation accuracy with respect to the number of epochs. The loss comparison graphs of various CNN classification algorithms are shown in Figure 4.

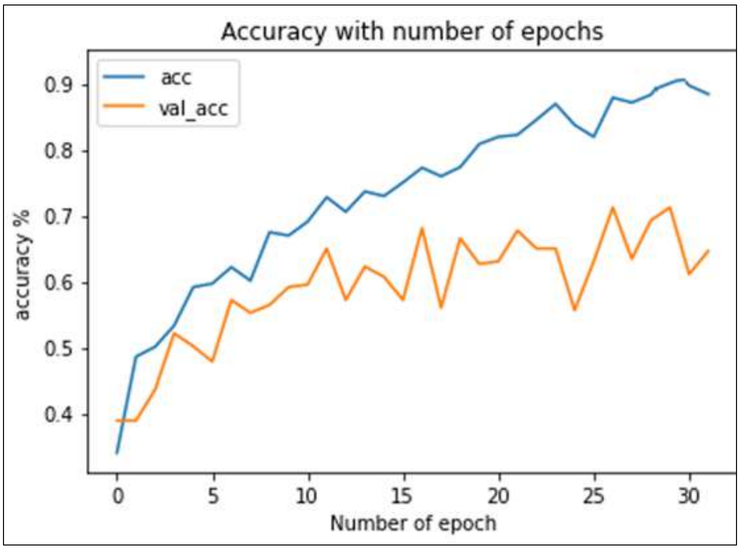

Fig 3: Accuracy and Validation Accuracy of CNN classifier

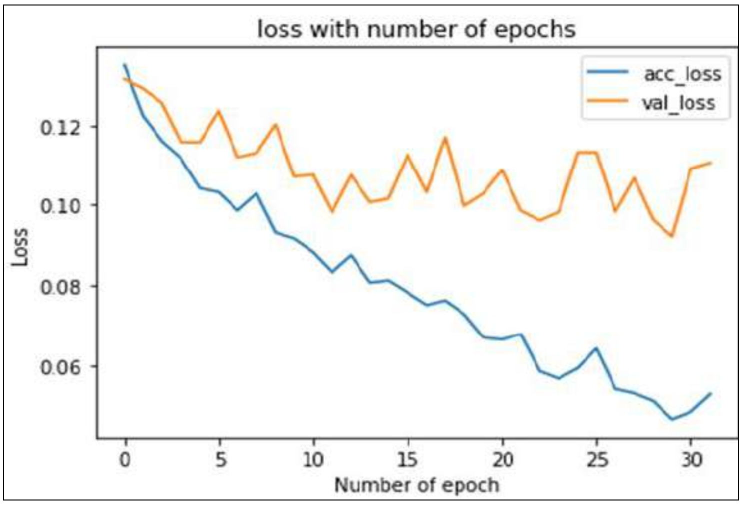

Fig 4: Loss Comparison graphs of CNN classifiers

5. Conclusions

Within the scope of this study, a Convolutional Neural Network (CNN) model for the diagnosis of skin cancer was created, constructed, and evaluated using a well-known melanoma dataset. Our proposed method, which is a two-stage learning platform, has great-predicted accuracy at each stage, as demonstrated by its overall accuracy of 88.83 percent. This is true not only for classification algorithms such as DT, RF, GBT.

The strategy that has been suggested is based on CNN, and it is possible to think of it as an effective method of multi-class categorization. In terms of melanoma classification accuracy, the modular and hierarchical structure of our CNN classifier not only beats state-of-the-art machine learning techniques, but it significantly minimises the amount of computational effort that is required. The fact that this strategy is only tested on a single dataset is one of the method's drawbacks.

6. References

1. Zhang Ce, Xin Pan, Huapeng Li, Gardiner A, Sargent I, Jonathon S Hare, *et al*. A hybrid MLP-CNN classifier for very fine resolution remotely sensed image classification. Isprs Journal of Photogrammetry and Remote Sensing. 2017;140:133-144.
2. Bi Lei, Jinman Kim, Euijoon Ahn, Feng D. Automatic Skin Lesion Analysis using Large-scale Dermoscopy Images and Deep Residual Networks. ArXiv abs. 2017;1703:04197.
3. Yuan Y, Lo YC. Improving Dermoscopic Image Segmentation with Enhanced Convolutional-De convolutional Networks. IEEE J Biomed Health Inform. 2019 Mar;23(2):519-526. DOI: 10.1109/JBHI.2017.2787487. Epub 2017 Dec 25. PMID: 29990146.
4. Feng-ying Xie, Jiawen Yang, Liu J, Zhi-guo Jiang, Yushan Zheng, Yukun Wang. Skin lesion segmentation using high-resolution convolutional neural network. Computer methods and programs in biomedicine. 2020;186:105241.
5. Yao Y, Luo Z, Li S, Fang T, Quan L. MVSNet: Depth Inference for Unstructured Multi-view Stereo. In: Ferrari V., Hebert M., Sminchisescu C., Weiss Y. (eds) Computer Vision – ECCV 2018. ECCV 2018. Lecture Notes in Computer Science, 2018, 11212. Springer, Cham. https://doi.org/10.1007/978-3-030-01237-3_47
6. Li Y, Shen L. Skin Lesion Analysis towards Melanoma Detection Using Deep Learning Network. Sensors (Basel). 2018 Feb 11;18(2):556. DOI:

10.3390/s18020556. PMID: 29439500; PMCID: PMC5855504.

7. Rashmi Patil, Sreepathi Bellary. Machine learning approach in melanoma cancer stage detection, Journal of King Saud University - Computer and Information Sciences, 2020, ISSN:1319-1578, https://doi.org/10.1016/j.jksuci.2020.09.002.
8. Konstantin Korotkov, Josep Quintana, Ricard Campos, Am´erica Jes´us-Silva, Pablo Iglesias, Susana Puig, *et al*. An Improved Skin Lesion Matching Scheme in Total Body Photography, IEEE Journal of Biomedical and Health Informatics. 2019 Mar;23(2):586-598.
9. Kassem MA, Hosny KM, Fouad MM. Skin Lesions Classification into Eight Classes for ISIC 2019 Using Deep Convolutional Neural Network and Transfer Learning, in IEEE Access. 2020;8:114822-114832. DOI: 10.1109/ACCESS.2020.3003890.
10. Ichim L, Popescu D. Melanoma Detection Using an Objective System Based on Multiple Connected Neural Networks, in IEEE Access. 2020;8:179189-179202. DOI: 10.1109/ACCESS.2020.3028248.
11. Patil R, Bellary S. Transfer learning based system for melanoma type detection. Revue d'Intelligence Artificielle. 2021;35:(2):123-130. https://doi.org/10.18280/ria.350203
12. Ravi V, Pradeepkumar D, Deb K. Financial time series prediction using hybrids of chaos theory, multilayer perceptron and multi-objective evolutionary algorithms. Swarm Evolut Comput. 2017;36:136-149.