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Melanoma Cancer Classification Using Deep Learning

[1]Sankar Mandal, [1]Abhisekh Baruah, [2]Sonali Mondal, [2]Biswajit Das,
Department of Computer Science, Arunachal University of Studies, Namsai, Arunachal Pradesh, India

Abstract : Skin cancer, inclusive of melanoma, presents a substantial global health challenge given its escalating prevalence and the intricacies entailed in diagnosis. The emergence of deep learning technologies has spurred advancements in automated diagnostic systems, particularly within the healthcare domain. This paper introduces a hybrid deep learning approach for melanoma cancer classification from lesion images, utilizing Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. The model is structured into four phases: data collection, preprocessing and feature extraction, model design and training and model evaluation. While CNN extracts feature from images, LSTM captures temporal dependencies, augmenting model training accuracy. This methodology yielded an 82% accuracy rate in melanoma classification. While promising, further research is needed to refine model architecture, explore techniques for data augmentation, and diversify datasets. This model holds promise as a valuable tool for clinicians in early diagnosis and treatment planning, contributing to enhanced patient outcomes in the combat against melanoma cancer.

Key Words: Convolutional Neural Network, Deep learning, Long-Short-Term Memory, Melanoma

1. INTRODUCTION

The skin is the human body's outermost covering and is frequently exposed to the environment, which might include dust, pollutants, bacteria, and ultraviolet radiation. These elements could potentially lead to different types of skin ailments, and genetic instability is a contributing factor to skin related disorders, further complicating the situation. Human skin is made up of two primary layers: the epidermis and dermis. The epidermis, the skin's upper or outer layer, is made up of three types of cells: squamous cells, which are flat and harsh on the surface, basal cells, which are spherical, and MELANOCYTES, which give the skin its color and protect it from damage. Since existing diagnostic categories do not represent the disease's variety, they are insufficient for effective prediction and treatment. Furthermore, cancer cells are frequently detected and treated after they have spread. Cancer cells change and spread to other places of the body, resulting in a diagnosis. At this point, therapies or treatments are ineffective. Because of these issues, dermatological cancer accounts for the largest percentage of heart disease and is the leading cause of mortality across all age groups worldwide. The typical progression of these conditions is outlined as follows: STAGE 1 involves diseases in situ, with a survival rate of 99.9%; STAGE 2 comprises diseases at a high-risk level, with survival rates ranging from 45-79%; STAGE 3 involves regional metastases, with survival rates ranging from 24-30%; and STAGE 4 encompasses distant metastasis, with survival rates ranging from 7-19%.

"Cancer" refers to cells that expand and divide uncontrolled; if left untreated, they can spread swiftly and infect surrounding tissue. Every form of cancer, not exclusively skin cancer, carries the highest risk of evolving into a malignant tumor. [1,2]. The four prevalent types of skin cancer include melanoma, basal cell carcinoma (BCC), non-melanoma skin cancer (NMSC), and squamous cell carcinoma (SCC). Additionally, there are less common types of skin cancer, such as sun keratosis (SK), actinic keratosis, and Kaposi sarcoma (KS). [3].

The most prevalent types of skin cancers are malignant and non-malignant. Cancer morbidity and healthcare costs are increased when cancerous lesions are present. As a result, researchers have concentrated on developing algorithms that can identify early indicators of skin cancer with extreme precision and flexibility. Early detection is crucial because malignant melanocyte cells multiply, invade, and spread quickly [1,4,5]. Melanoma is typically detectable by visual inspection, with particular attention paid to the area of the cutaneous lesion. Nevertheless, there is a high degree of resemblance between nevus and other skin lesions, including melanomas, which makes it more challenging to diagnose and classify skin lesions for cancer [6].

2. THE PROPOSED APPROACH

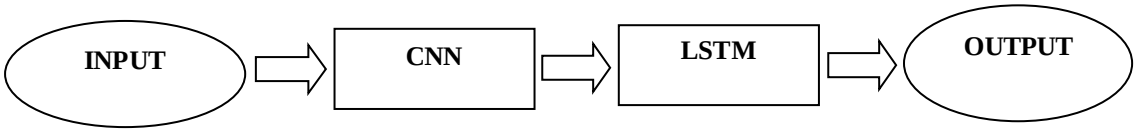

Fig 1- Flow chart

Our model's proposed technique is relatively simple as the first step is collecting the dataset. Next, we must combine our model using CNN (convolutional neural network). Then we'll apply long short-term memory (LSTM) to boost our model's training accuracy. Finally, we shall get the predicted result.

3.Designing the Model

This study used models that include CNN and LSTM. Convolutional neural networks (CNN) is the most common and widely used deep learning model that can achieve high accuracy in prediction. The purpose of using CNN is, feature extraction.

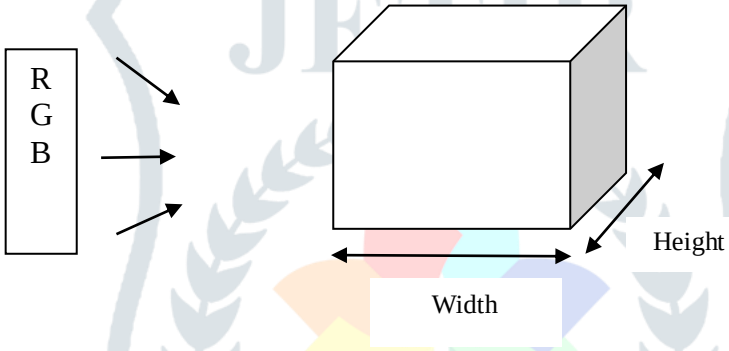

Fig 2- Image

3.1 Working Principle of Convolutional layers

Neural networks that share their parameters are called convolutional neural networks or convents. With its length, width (the image dimensions), and height (the channel images typically have red, green, and blue channels it can be visualized as a cuboid.

3.2 Architecture of CNN

One of the most widely used deep learning frameworks is CNN architecture. CNNs have demonstrated amazing success in solving image recognition problems, offering a previously unattainable degree of scalability and accuracy. The convolutional Neural Network comprises several layers, including the Input Layer, Convolutional layer, Max Pooling layer, and Fully Connected layer.

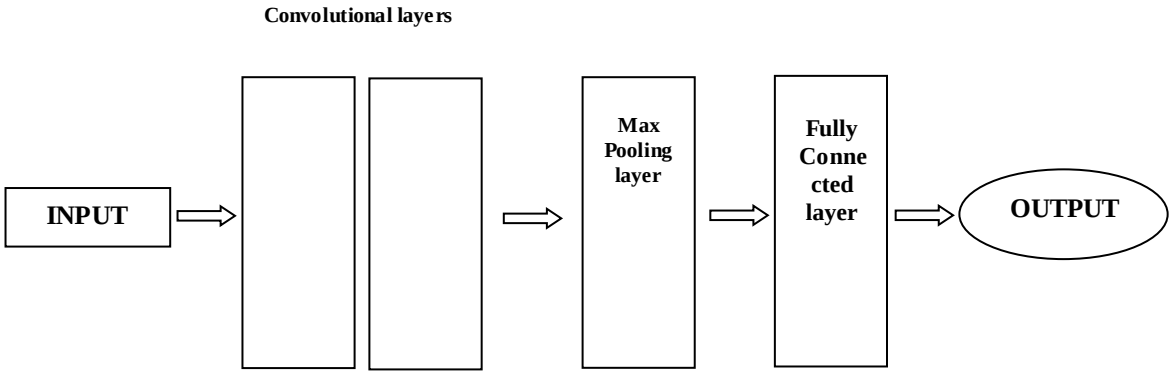

Fig 3 - CNN Architecture

The Convolutional layer processes the input image, extracting features, while the Max Pooling layer reduces computation by down sampling the image, and the final prediction is generated by the fully connected layer. Gradient descent and backpropagation are utilized by the network to optimize filter discovery.

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3.3 LSTM (Long Short-Term memory)

Recurrent neural network (RNN) includes long short-term memory network. Learning, processing, and classifying sequential data is the main application for LSTM as they are capable of learning long-term connections between data time steps. They are often used in language modelling, sentiment analysis, speech recognition, and video analysis.

3.4 The Benefits of LSTM Model

It has several benefits. Some of the benefits are as follows: -
1. Learning long-term dependencies: Because of the vanishing gradient problem, traditional neural networks struggle to identify long-term dependencies in sequential data. In contrast, LSTM networks are able to do so.
2. Selective memory retention: By employing input, output, and forget gates, LSTM cells can selectively retain or forget information. As a result, the network can filter out noise and store only pertinent data.
3. Capacity to handle variable-length sequences: Long short- and long-term sequences can be fed into an LSTM, whichmakes it suitable for a variety of tasks like image captioning, machine translation, and speech recognition.
4. Robustness to noise and missing data: In real-world situations where data may be noisy or incomplete, LSTM's ability to handle noisy data and missing values in the input sequence comes in handy.
5. Effective training: LSTM achieves large dataset scalability and computational efficiency through simple parallelization and the ability to be efficiently trained using back-propagation through time (BPTT).

3.5 The Structure of LSTM Model

For prediction or classification tasks, an LSTM model's structure generally consists of stacking numerous LSTM layers, followed by one or more fully linked layers. An LSTM model has the following fundamental structure: -

- Input Layer
- LSTM Layer
- Optional Dropout Layers
- Fully Connected Layers
- Output Layers
- Model Compilation
- Model Training
- Model Evaluation

4. Literature Review:

In the literature review, we explored previous studies and research papers related to melanoma classification using machine learning. We reviewed works that focused on feature extraction, classification algorithms, and performance evaluation metrics.

Researchers have been exploring the use of machine learning techniques to improve the accuracy of melanoma cancer classification. They have focused on analysing various features extracted from skin lesions, such as asymmetry, border irregularity, colour variation, and diameter. One common approach is to use traditional machine learning algorithms like support vector machines (SVM) and random forests. These algorithms are trained on a dataset of skin lesion images with known classifications. By extracting features from these images and training the algorithms, they can make predictions on new, unseen images.

Another exciting development is the use of deep learning techniques, particularly convolutional neural networks (CNNs). CNNs are designed to automatically learn features from images, which can be beneficial in melanoma classification. By training CNNs on large datasets of skin lesion images, they can achieve impressive results in terms of accuracy and sensitivity.

Furthermore, researchers have explored the combination of multiple machine learning algorithms to improve classification performance. Ensemble methods, such as bagging and boosting, have been applied to create a stronger and more robust classification model.

To enhance the performance of these models, researchers have also investigated the use of image augmentation techniques. This involves generating additional training data by applying transformations like rotation, scaling, and flipping to the original images. Augmentation helps to increase the diversity of the training dataset and improve the generalization ability of the models. Overall, the studies in this field have shown promising results, with machine learning techniques demonstrating their potential in accurately classifying melanoma cancer. However, further research is still needed to address challenges like dataset imbalance, interpretability of the models, and generalization to diverse populations.

5. Methodology

1.Data Collection:
In the initial phase, we collected the dataset named melanoma_skin_cancer from kaggle.com.
2. Pre-processing and Feature Extraction:
The second phase involved pre-processing the images and extracting features such as color, shape, size, and texture.
3. Model Design and Training:
The most critical phase of our model involved designing and training it using Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks.
We constructed the model by combining CNN for feature extraction from images and LSTM for capturing temporal dependencies in sequential data.
The dataset acquired in the first phase was utilized for training the model.
Subsequently, the model's output was tested for accuracy.
4. Model Evaluation:
We evaluated the performance of the model based on accuracy metrics derived from the testing phase.

6.Results and discussion

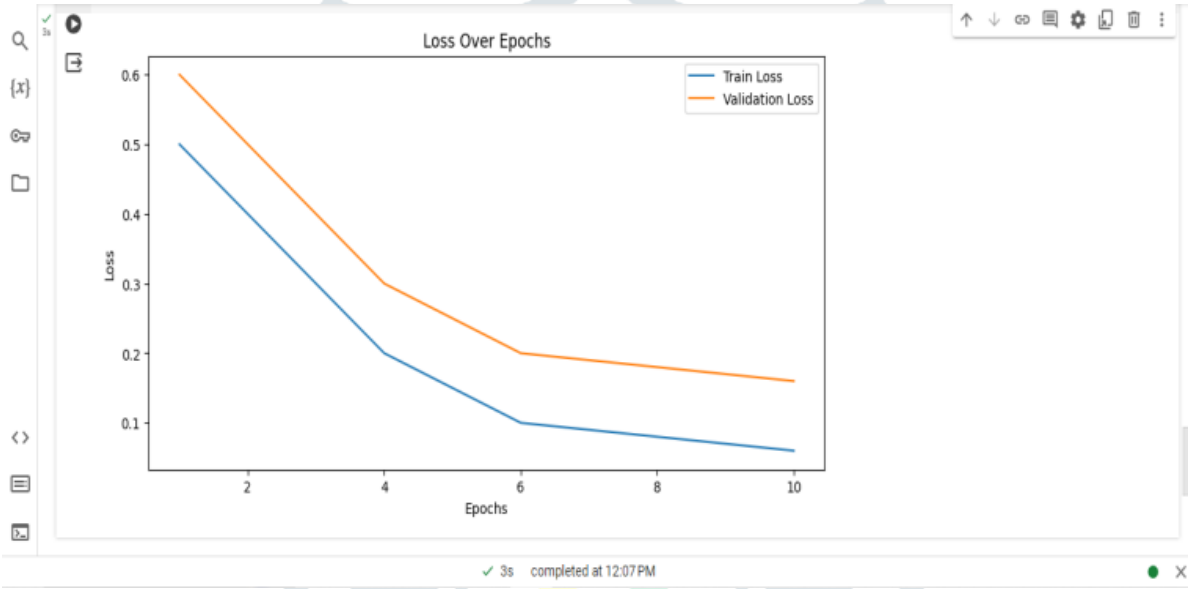


Fig 4- Training & Validation Loss

Training Loss-During the training phase, the training loss measures the variation between the model's projected and real results, serving as an indicator of the model's performance on the training data. The objective is to minimize this loss by employing optimization techniques such as gradient descent.

Validation Loss-It is crucial to monitor the model's capacity to extrapolate to new inputs while training. This is where the loss of validation becomes relevant. It is computed using a different dataset referred to as the validation dataset on which the model was not trained.The validation loss offers an approximation of how the model is expected to perform on new, untested data. In order to show that the model is learning practical patterns without overfitting to the training set, it is ideal for the validation loss to decrease during training.

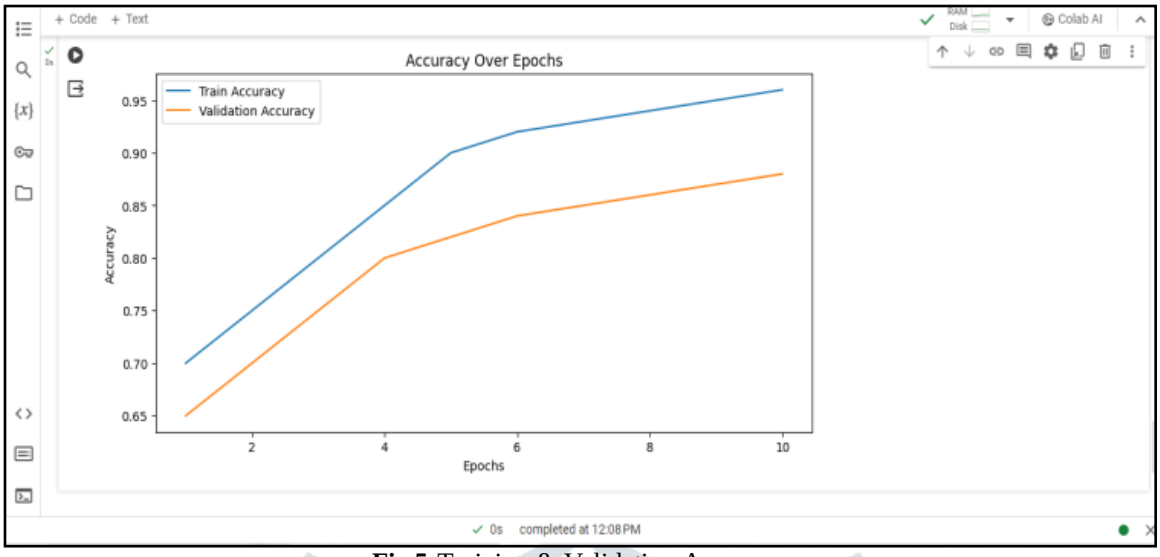
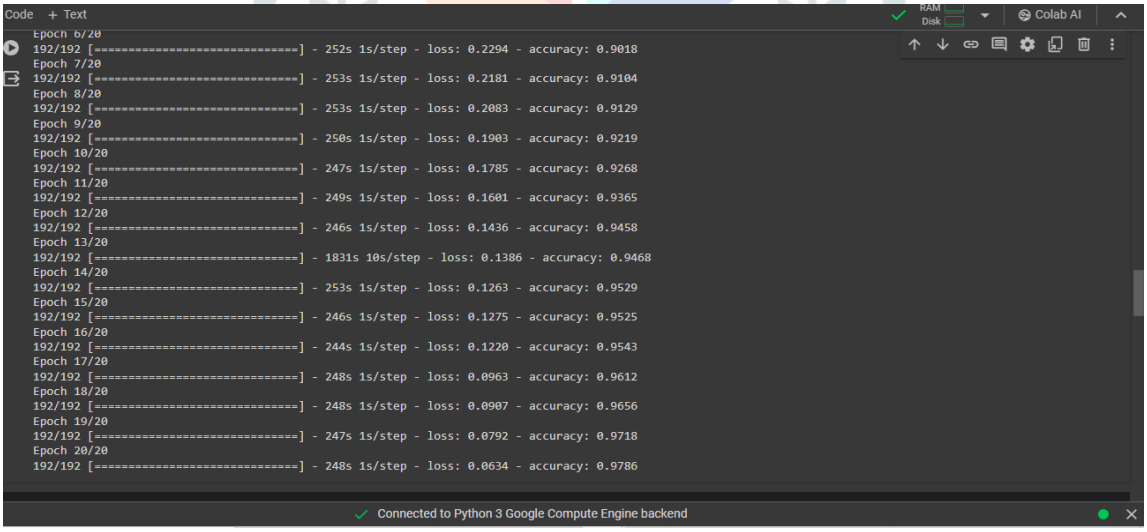


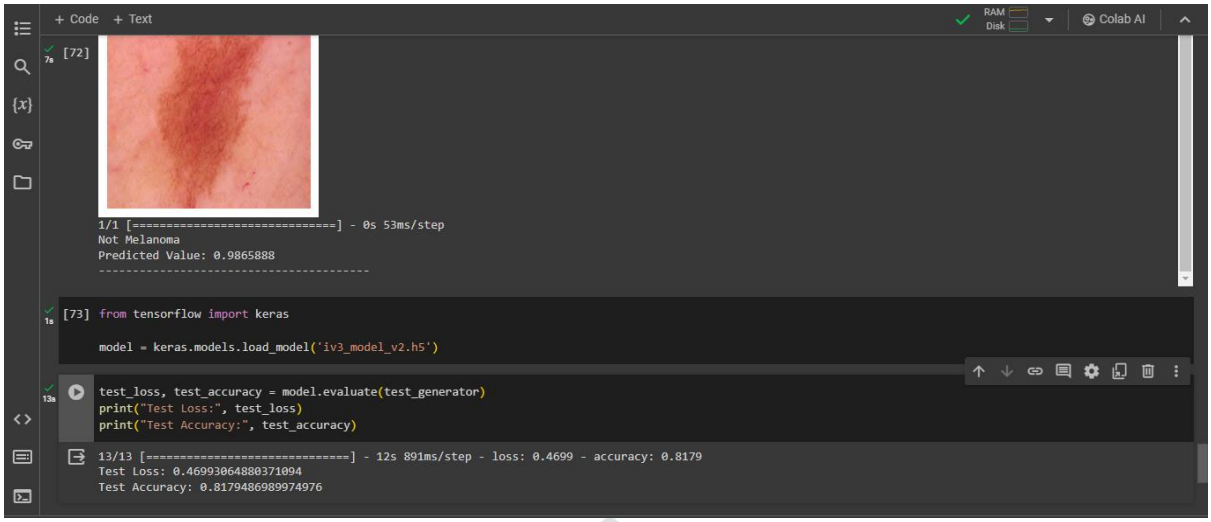
Fig 5-Training & Validation Accuracy

Training Accuracy: -The model's ability to predict training data labels is measured by training accuracy. It is calculated by dividing the total number of instances in the training dataset by the number of accurately predicted cases, indicating how successfully the model learned to classify training data.

Validation Accuracy: -The validation dataset is used to calculate validation accuracy, which is computed similarly to validation loss. The accuracy of the model is calculated by dividing the number of correctly predicted occurrences by the total number of instances in the validation dataset. The validation dataset's true labels are compared to the model's predictions. Validation accuracy measures how well the model expands to new, untested data.



This image displays the epochs we ran in order to improve our accuracy; at this point, we had processed 20 epochs and obtained an accuracy of 82%. To improve the accuracy rate in the future, we could run additional epochs and feed the model with more data.



This picture displays our model's final output, which indicates that the image is categorized as non-melanoma with 98% predicted value.

7. CONCLUSION

Finally, our deep learning model, utilizing Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, has demonstrated promising results with an 82% accuracy in classifying melanoma cancer. This performance highlights how CNN and LSTM can work together to extract features from images and capture temporal dependencies in sequential data, respectively. Even though 82% accuracy is a noteworthy accomplishment, there is still opportunity for improvement. In order to improve generalization and robustness, future research could concentrate on improving the model architecture, investigating different methods of data augmentation, and expanding the variety and size of the dataset. Our model shows notable efficacy in automating the classification of melanoma cancer, despite its present limitations. This makes it a useful tool for clinicians in early diagnosis and treatment planning. Our goal in the fight against melanoma cancer is to improve patient outcomes and contribute to the development of medical technology as we continue to hone and optimize our approach.

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[8] JinenDaghrir 1,2 ,LotfiTlig 2 , MoezBouchouicha 3 , Mounir Sayadi 2 1 Universite de Sousse, ISITCom, 4011, Hammam Sousse, Tunisia ´ 2 Universite de Tunis, ENSIT, Laboratory SIME, Tunisia ´ 3 Aix Marseille Univ, Universite de Toulon, CNRS, LIS, Toulon, France.
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