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DEEP LEARNING BASED APPROACH FOR DETECTION OF MELANOMA AND NON-MELANOMA FROM DERMASCOPIC IMAGES

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ABSTRACT

Amid growing concerns about global skin diseases, there is an urgent need for innovative applications to mitigate their impact and improve overall skin health. Skin problems, stemming from a combination of genetic factors and environmental influences, underscore the global significance of effective diagnosis and treatment. Theproblem statement is to figure out if a skin issue is the serious kind called melanoma ornot, so we can treat it the right way. Current diagnostic approaches relying on Gaussian Naive Bayes models reveal limitations in accuracy and sensitivity, necessitating a transformative shift. The research advocates for a paradigm change towards a Deep Learning-Based Automated Classification system, specifically leveragingConvolutional Neural Networks (CNNs) for heightened precision in classifying melanoma and non-melanoma skin diseases from dermascopic images. The proposed methodology entails importing dermoscopic image data, implementing tailored preprocessing, and defining variables before applying CNNs to extract intricate patterns. Performance metrics, including accuracy and confusion matrix, gauge the model's efficacy compared to the Gaussian Naive Bayes model. By transitioning to a deep learning approach, this study aims to overcome the limitations of the current Gaussian Naive Bayes model, providing a more sophisticated and automated solution for precise skin disease classification. The primary objective is to contribute to the reduction of skin disorders, offering an efficient tool for classifying melanoma or non-melanoma skin diseases and thereby enhancing public health outcomes.

Keywords: Skin diseases, Melanoma, Non-melanoma, Deep learning, Convolutional Neural Networks.

1. INTRODUCTION

1.1 Overview

The aim of employing a deep learning approach for the detection of melanoma and non-melanoma skin diseases from Dermascopic images is rooted in the urgent need for more accurate, efficient, and accessible diagnostic methods. Skin disorders, particularly melanoma, pose a significant public health concern, and early detection is paramount for effective treatment. Traditional methods of classification, often reliant on manual examination by dermatologists, are associated with limitations such as subjectivity, expertise dependency, and time-consuming processes. In response to these challenges, the proposed deep learning approach leverages advanced techniques, specifically Convolutional Neural Networks (CNNs), to automate the classification of Dermascopic images. This approach aims to overcome the drawbacks of conventional methods by introducing a data-driven model that can discern intricate patterns and features indicative of melanoma or non-melanoma skin diseases. By utilizing deep learning, thesystem can learn and adapt to diverse image variations, leading to enhanced accuracy and efficiency in the classification process. The overview of this deep learning approach involves several key steps. Firstly, Dermascopic images are imported into the system. Subsequently, image preprocessing techniques are applied to enhance the quality and relevance of the data. The process then moves to defining independent and dependent variables, crucial for training the deep learning model. Data splitting is employed to ensure the model's effectiveness is evaluated accurately. The heart of the approach liesin the application of CNNs, which are adept at recognizing patterns and features in images. Performance metrics, including accuracy and confusion matrix, are calculated to assess the reliability of the model.In summary, the deep learning approach for the detection of melanoma and non-melanoma from Dermascopic images aims to revolutionize skin disease diagnosis by providing a more objective, efficient, and automated solution. By combining advanced technology with medical imaging, this approach holds the potential to significantly improve early detection rates, contribute to timely intervention, and ultimately reduce the burden of skin disorders on public health.

1.2 Problem Statement

The primary concern we're facing is with the existing methods for identifying and classifying skin diseases, specifically melanoma and non-melanoma. Currently, dermatologists use a tool called a dermoscope to examine pictures of the skin and determine the nature of the skin problem. However, this manual process has its drawbacks—it tends to be slow, not always highly accurate, and heavily relies on the expertise of the individual doctor. Given the increasing prevalence of skin problems, particularly serious ones like melanoma, there's a pressing need for a more effective and quicker diagnostic approach. The complexity of skin conditions is exacerbated by variations in appearance from person to person, making the current methodology less reliable. The desire is for a more intelligent system that can address these challenges.

This is where the deep learning approach enters the picture. Instead of depending solely on human judgment, we are incorporating computer technology, specifically Convolutional Neural Networks (CNNs), to develop a system that can learn from a vastarray of skin images. The objective is to create an automated system capable of accurately determining whether a skin issue is melanoma or another type of problem. To achieve this, the computer is trained with a diverse set of skin images, enabling it torecognize crucial details associated with melanoma and other skin conditions.

In simpler terms, the core challenge lies in finding a more efficient and quicker methodto diagnose skin diseases. The current reliance on manual examination has its shortcomings, and by integrating intelligent computer technology that learns from numerous images, we aim to enhance the reliability and speed of the diagnostic process. The envisioned outcome is a transformative shift in how we identify and address skin conditions, particularly severe ones like melanoma, with the potential for earlier and more manageable interventions. This advancement could significantly impact the field, making skin disease diagnosis more accessible to a broader population.

1.3 Research Motivation

The motivation behind researching a deep learning approach for the detection of melanoma and non-melanoma from Dermascopic images stems from the critical need to address the limitations and challenges prevalent in traditional diagnostic methods. Skin cancers, especially melanoma, are known for their potential lethality, and early detection plays a pivotal role in successful treatment. The current reliance on guassian naive bayes model by dermatologists presents inherent shortcomings, including subjectivity, dependence on individual expertise, and the considerable time investment required for accurate classification. As the incidence of skin disorders continues to rise globally, there is a growing urgency to develop more advanced and efficient diagnostic tools. Traditional methodologies fall short in providing a scalable and reliable solution, particularly concerning the intricate and nuanced nature of Dermascopic images. Variability in lesion appearance and the complexity of skin conditions demand a more sophisticated approach that can discern subtle patterns indicative of different diseases. The motivation for adopting a deep learning approach lies in its potential to revolutionize the field of dermatological diagnostics. By leveraging Convolutional Neural Networks (CNNs), researchers aim to create a system that can autonomously learn and recognize intricate patterns and features associated with melanoma and non-melanoma skin diseases.

This approach has the advantage of being data-driven, allowing the model to adapt to diverse and complex variations in Dermascopic images, ultimately enhancing accuracy and efficiency in disease classification. Moreover, the deep learning approach aligns with the broader trend in artificial intelligence applications in healthcare, where advanced technologies are increasingly being utilized to augment human capabilities inmedical diagnostics.

The integration of deep learning in skin disease detection not only addresses the currentshortcomings but also holds the promise of providing a more objective, consistent, and timely diagnostic methodology. In summary, the research motivation for a deep learning approach in the detection of melanoma and non-melanoma from Dermascopic images is grounded in the pressing need for improved diagnostic accuracy, efficiency, and scalability. By embracing the capabilities of deep learning, researchers aspire to contribute to early disease detection, better patient outcomes, and a transformative shiftin how we approach the diagnosis of skin disorders.

2. LITERATURE SURVEY

Gajera, et al. [1] proposed an automated framework that extracted visual features from Dermascopic images using a pre-trained deep CNN model and then employed a set of classifiers to detect melanoma. Recently, few pre-trained CNN architectures were employed to extract deep features from skin lesions. However, a comprehensive analysis of such features derived from a variety of CNN architectures had not yet been performed for melanoma classification. Therefore, in this paper, they investigated the effectiveness of deep features extracted from eight contemporary CNN models. They also explored the impact of boundary localization and normalization techniques on melanoma detection. The suggested approach was evaluated using four benchmark datasets: PH2, ISIC 2016, ISIC 2017, and HAM10000. Experimental outcomes indicated that DenseNet-121 with a multi-layer perceptron (MLP) achieved a higher performance in terms of accuracy of 98.33%, 80.47%, 81.16%, and 81% on PH2, ISIC2016, ISIC 2017, and HAM10000 datasets compared to other CNN models and state- of-the-art methods.

Zhou, et al. [2] proposed MuSClD in the context of the automated diagnosis of non- melanoma skin cancer (NMSC). Specifically, they evaluated MuSClD for identifying and distinguishing (a) basal cell carcinoma (BCC), (b) in-situ squamous cell carcinomas(SCC-In Situ), and (c) invasive squamous cell carcinomas (SCC-Invasive), using an Australian (training, n = 85) and a Swiss (held-out testing, n = 352) cohort. Their experiments revealed that MuSCID reduced the Wasserstein distances between sites in terms of colour, contrast, and brightness metrics, without imparting noticeable artifacts to training data.

Albraikan, et al. [3] conducted study, an automated deep learning-based melanoma detection and classification (ADL-MDC) model was proposed. The primary objective of the ADL-MDC technique was to analyse Dermascopic images and ascertain the presence of melanoma.

Wamane, et al. [4] proposed methodology involved the creation of CNN and ResNet- 50 models, along with the application of various pre-processing methods. Hair removal and augmentation procedures were utilized, enabling the CNN and ResNet-50 models to accurately identify melanoma in Dermascopic photographs with respective accuracies of 98.07% and 99.83%. Furthermore, the models, employing the hair removal method, achieved accuracies of 97.06% and 100% for non-Dermascopic images. Additionally, by incorporating age and sex as supplementary criteria, the CNN model achieved an accuracy of 96.40% in the identification of melanoma in dermoscopic images. These findings suggest that the developed models could serve asvaluable tools for the early detection of melanoma, crucial for effective treatment and the prevention of fatalities.

Nigar, et al. [5] In the study, proposed a novel model based on deep learning to diagnoseskin diseases at a preliminary stage using classification. The developed model successfully identified six different skin diseases, namely, actinic keratosis, benign keratosis, melanoma, basal cell carcinoma, insect bites, and skin acne. Various state- of-the-art algorithms were examined on benchmark datasets, including the InternationalSkin Imaging Collaboration (ISIC) 2019 dataset and the UCI Data Centre, assessing accuracy, precision, recall, and F1-score metrics. The results revealed that the convolutional neural network (CNN) demonstrated distinct superiority over its peers, achieving an accuracy rate of 97%, precision of 91%, recall of 91%, and an F1-score of91%.

Sivakumar, et al. [6] proposed the model eliminated unwanted noise, enhanced spectral image information, and improved classification accuracy through preprocessing and mixed hybrid pooling phases. Performance analysis indicated that the Malignant Melanoma Cancer detection model achieved the highest accuracy of 94% and an F1- score of 93.9%.

Ali Shah, et al. [7] proposed the integration of long short-term memory (LSTM), Bi- directional LSTM (BLSTM), and gated recurrent unit (GRU) architectures for the detection of mutations in cutaneous melanoma. The dataset used in the study contained2608 human samples and a total of 6778 mutations, spanning 75 types of genes.

Sauter, et al. [8] proposed deep learning methodology was later adopted in this field, but it still lacked the wider adoption of deep learning (DL) methods that had already proven effective for other applications. The discussion also touched upon upcoming trends towards ImageNet-based feature extraction and the utilization of larger models. Although DL had achieved human-competitive accuracy in routine pathological tasks, its performance on advanced tasks remained inferior to wet-lab testing, for example. Finally, the challenges impeding the translation of DL methods to clinical practice wereexplored, and insights into future research directions were provided.

Nambisan, et al. [9] proposed an approach that facilitated leveraging the strengths of both deep learning and conventional image processing techniques to improve the accuracy of melanoma diagnosis. The study suggested that further research combiningdeep learning with conventional image processing on automatically detected Dermascopic features is warranted.

Rahman, et al. [10] proposed the method was then employed on two datasets, namely ISIC 2017 and the academic torrents dataset. The results showed that their proposed method achieved accuracy, sensitivity, and specificity rates of 99.85%, 91.65%, and 95.70%, respectively. This performance surpassed that of previously proposed machinelearning algorithms in the same domain.

Bharathi, et al. [11] proposed a parallel CNN architecture for the classification of skin images into either melanoma or healthy. Initially, a color map histogram equalization (CMHE) method was proposed in this article to enhance the source skin images. Subsequently, thick and thin edges were detected from the enhanced skin image usingthe Fuzzy system.

Tembhurne, et al. [12] proposed ensemble outperformed both expert dermatologists andother state-of-the-art deep learning and machine learning methods. Thus, this novel method could be of high assistance to dermatologists in helping prevent any misdiagnosis.

Sukanya, et al. [13] presented a new melanoma detection approach, comprised of threeforemost stages: segmentation, feature extraction, and detection. Starting with segmentation, a new algorithm called the Self Adaptive Sea Lion Algorithm (SA- SLnO) was used to improve the K-means clustering model's initial centroids in a way that maximized performance.

Gayatri, et al. [14] proposed model mainly focused on various deep learning techniques such as convolutional neural networks, recurrent neural networks, and You Only LookOnce for the purpose of classifying and predicting melanoma. It also focused on other variants of melanomas, namely ocular melanoma and mucosal melanoma, emphasizingthat the location where melanoma starts in the body is not a negligible factor.

Hussien, et al. [15] proposed deep learning (DL) approach had the potential to assist dermatologists in the early detection of MSC, leading to more effective treatment and improved patient outcomes. It also demonstrated the effectiveness of DL techniques for medical image analysis, emphasizing the importance of carefully designing and optimizing CNN models for high performance. The accuracy of the proposed system was 99.99%.

3. PROPOSED METHODOLOGY

3.1 Overview

The proposed methodology for the deep learning-based approach to detect melanoma and non-melanoma lesions from Dermascopic images leverages Convolutional NeuralNetworks (CNNs) as the foundational algorithm. The process begins with the collectionand preprocessing of a diverse dataset containing both melanoma and non-melanoma images. This dataset is then strategically split into training, validation, and test sets to facilitate robust model training and evaluation. For the model architecture, a CNN is chosen for its effectiveness in image classification tasks, and a pre-trained model, such as VGG, ResNet, or Inception, is employed to capitalize on transfer learning. Data augmentation techniques, including resizing, normalization, and augmentation, are applied to enhance the dataset's variability. The model undergoes transfer learning, fine- tuning its parameters on the dermoscopic dataset. Subsequently, training is conducted using appropriate loss functions and optimizers, with continuous monitoring on the validation set to prevent overfitting. Hyperparameter tuning is employed to optimize the model's performance. Evaluation metrics, including accuracy, precision, recall, F1 score, and area under the ROC curve, assess the model's generalization on the test set. Post-processing steps, such as thresholding or filtering implemented to refine predictions. Interpretability and explainability methods, like Grad-CAM or LIME, contribute to understanding the model's decisions. Ultimately, the validated model is deployed in clinical or real-world settings, adhering to ethical and regulatory guidelines. This comprehensive methodology aims to enhance the accuracy and reliability of melanoma detection from Dermascopic images through the integration of deep learningtechniques, particularly CNNs.

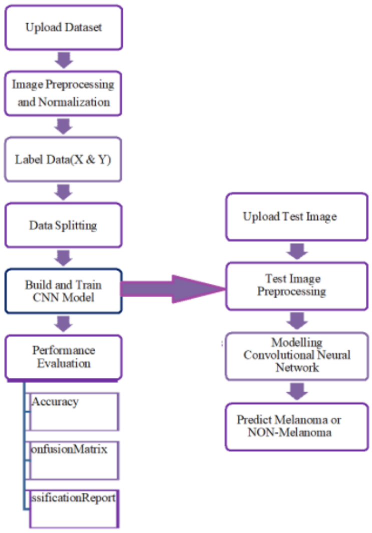


Figure 3.1: Block Diagram of Proposed System.

3.2 CNN

According to the facts, training and testing of CNN involves in allowing every source data via a succession of convolution layers by a kernel or filter, rectified linear unit (ReLU), max pooling, fully connected layer and utilize SoftMax layer with classification layer to categorize the objects with probabilistic values ranging from. Convolution layer is the primary layer to extract the features from a source image and maintains the relationship between pixels by learning the features of image by employing tiny blocks of source data. It's a mathematical function which considers two inputs like source image $I(x, y, d)$ where x and y denotes the spatial coordinates i.e., number of rows and columns. d is denoted as dimension of an image (here d=3 since the source image is RGB) and a filter or kernel with similar size of input image and can be denoted as $F(k_x, k_y, d)$..

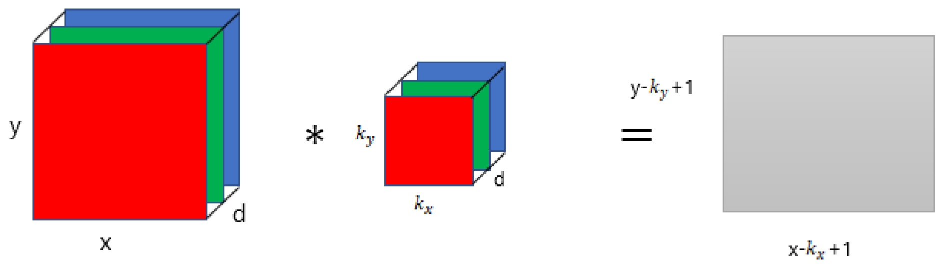
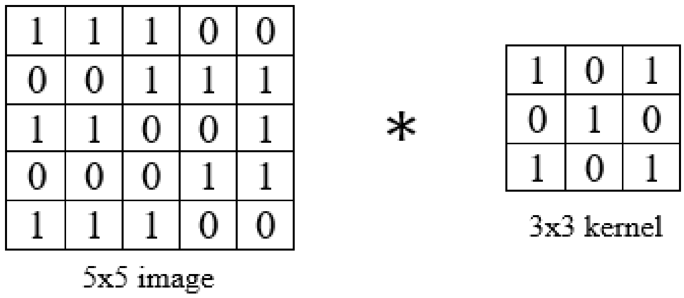
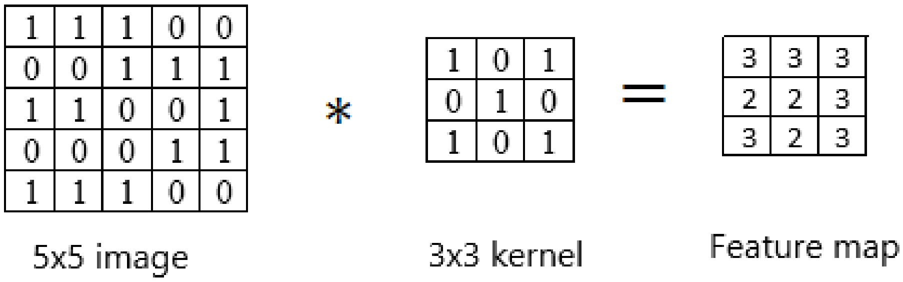


Fig. 3.2: Representation of convolution layer process.

The output obtained from convolution process of input image and filter has a size of $C\left((x - k_x + 1), (y - k_y + 1), 1\right)$, which is referred as feature map. Let us assume an input image with a size of 5×5 and the filter having the size of 3×3. The feature map of input image is obtained by multiplying the input image values with the filter values.



(a)



(b)

Fig. 3.3: Example of convolution layer process (a) an image with size 5×5 is convolving with 3×3 kernel (b) Convolved feature map.

ReLU layer

Networks those utilizes the rectifier operation for the hidden layers are cited as rectified linear unit (ReLU). This ReLU function $\mathcal{G}(\cdot)$ is a simple computation that returns the value given as input directly if the value of input is greater than zero else returns zero. This can be represented as mathematically using the function $max(\cdot)$ over the set of 0 and the input x as follows:

$$\mathcal{G}(x) = \max\{0, x\}$$

Max pooing layer

This layer mitigates the number of parameters when there are larger size images. This can be called as subsampling or down sampling that mitigates the dimensionality of every feature map by preserving the important information. Max pooling considers the maximum element form the rectified feature map.

Advantages of proposed system

- CNNs do not require human supervision for the task of identifying important features.
- They are very accurate at image recognition and classification.
- Weight sharing is another major advantage of CNNs.
- Convolutional neural networks also minimize computation in comparison with a regular neural network.
- CNNs make use of the same knowledge across all image locations.

4. RESULT AND DESCRIPTION

Figure 10.3: This figure provides an overview of the Graphical User Interface (GUI) designed for analyzing skin lesions of melanoma and non-melanoma. Users interact with this interface to perform various tasks related to dataset management, model training, and prediction. Figure 1: Demonstrating the initial step, this figure illustrates the process of uploading a dataset within the GUI. Users select the dataset file, which is then loaded into the interface for further analysis and processing. Figure 10.3.2: After the dataset is uploaded, this figure shows how the uploaded dataset is displayed within the GUI. Users can review the contents of the dataset to ensure accurate data loading. Figure 10.3.3: This figure depicts the preprocessing and normalization steps applied to the images in the dataset. Image preprocessing techniques are crucial for enhancing data quality and improving model performance.

Figure 1: Graphical User Interface of the skin lesions of melanoma and non-melanoma.

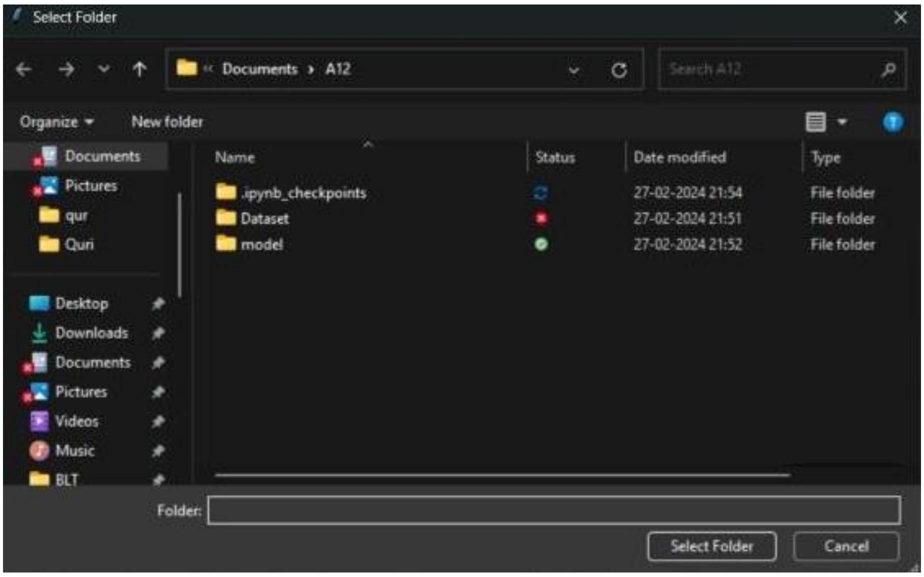


Figure 2: Uploading dataset in the Graphical User Interface.

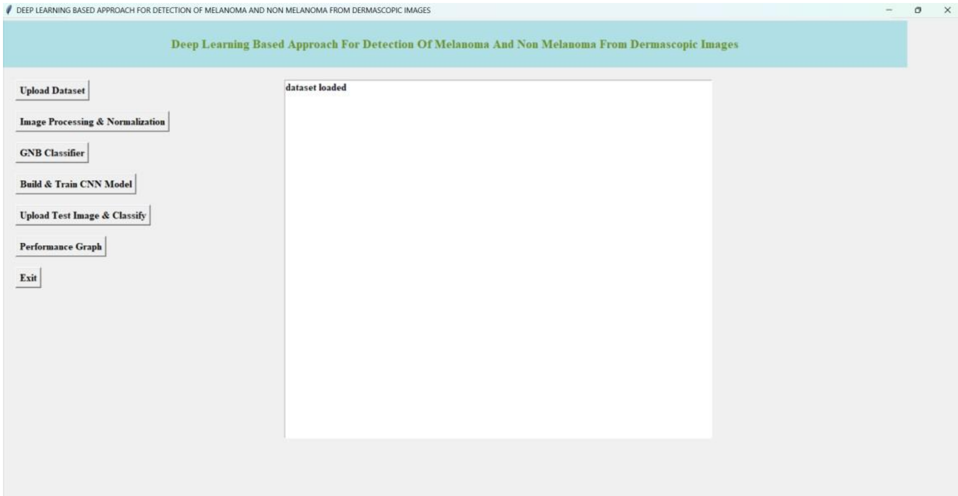


Figure 3: Dataset Uploaded is displayed on GUI

Figure 4: Image Preprocessing and Normalizations.

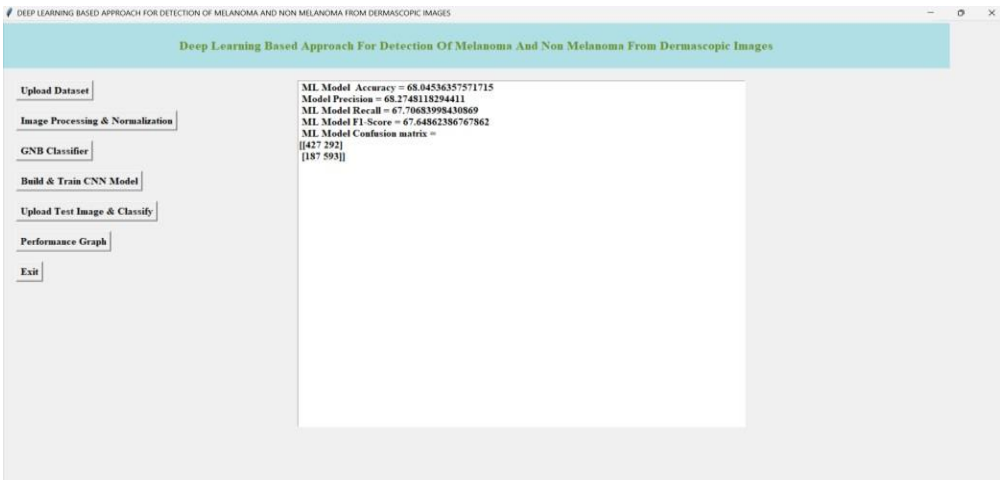


Figure 5: Performance metrics of GNB Classifier

Figure 10.3.4: Presenting the performance metrics of the Gaussian Naive Bayes (GNB) Classifier, this figure showcases the evaluation results obtained after training and testing the model. Performance metrics provide insights into the classifier's accuracy, precision, recall, and F1-score. Figure 10.3.5: Here, the figure displays the classification report and confusion matrix of the GNB Classifier. These metrics offer a detailed breakdown of the classifier's performance, including class-wise precision, recall, and F1-score, as well as a visual representation of prediction errors. Figure 10.3.6: Providing insights into the performance of the Convolutional Neural Network (CNN) model, this figure presents the performance metrics obtained after training and testing the CNN. CNNs are widely used for image classification tasks due to their ability to capture spatial hierarchies in data.

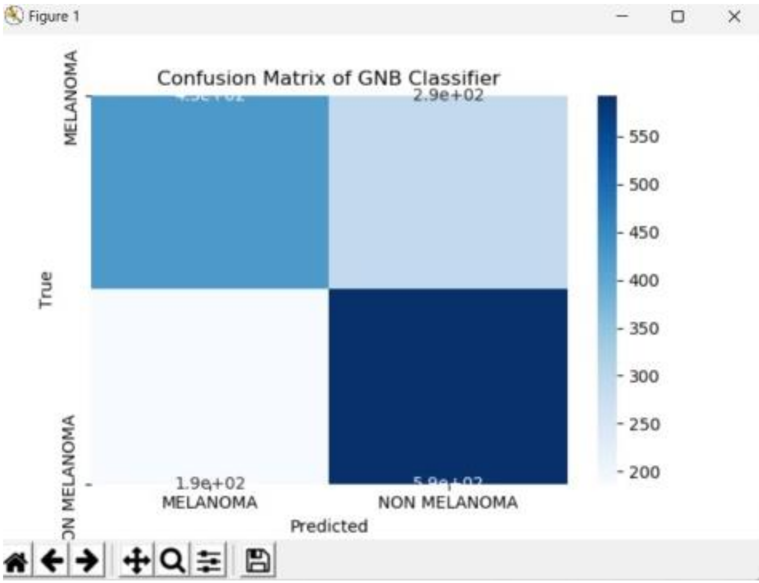


Figure 6: Classification Report and Confusion Matrix Of GNB.

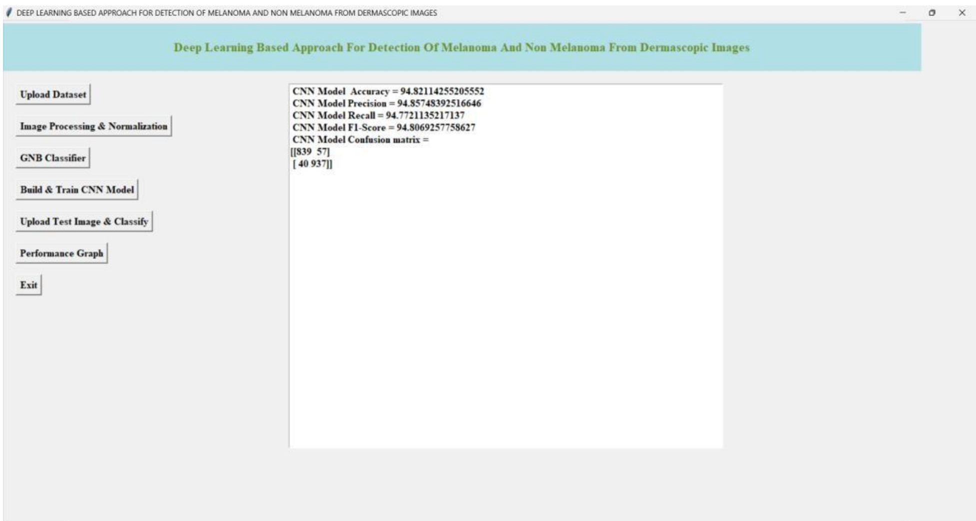


Figure 7: Performance metrics of CNN Model.

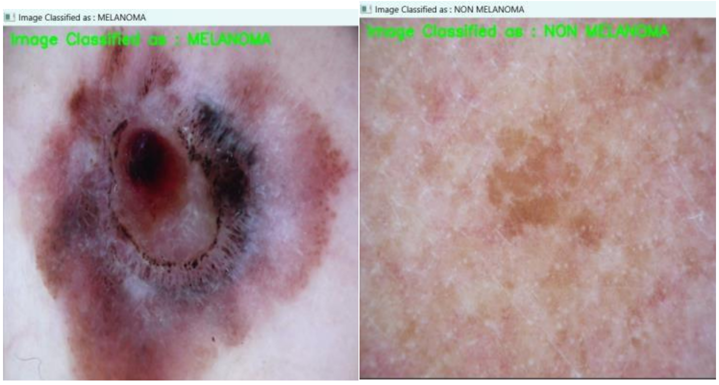


Figure 8: Model Prediction test Images.

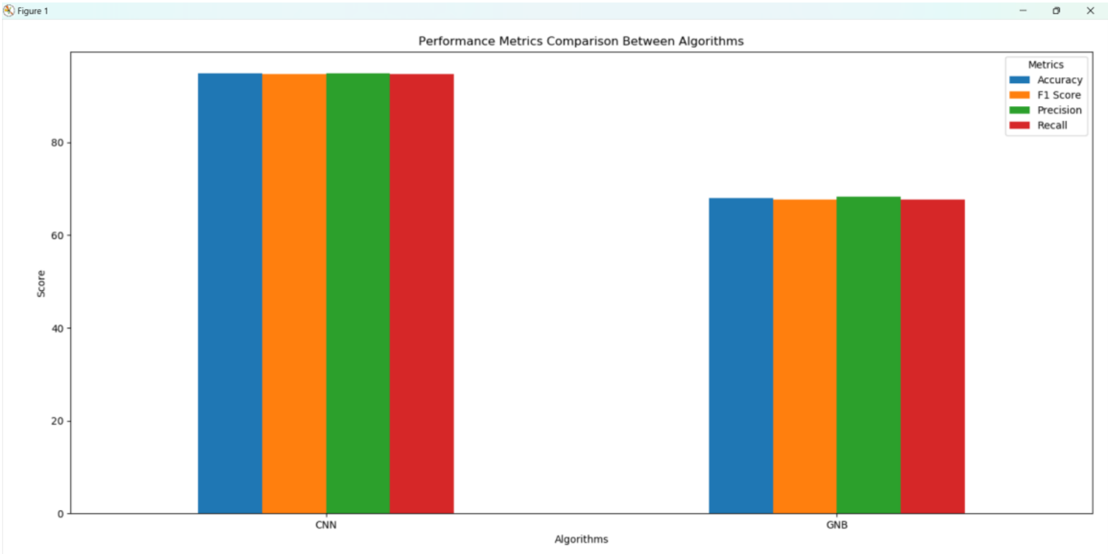


Figure 9: Performance Comparison Graph of CNN and GNB Models.

Figure 10.3.7: Users can observe the model's predictions on test images in this figure. The model utilizes learned features to classify skin lesions as melanoma or non-melanoma, aiding in early detection and diagnosis. Figure 10.3.8: This figure presents a performance comparison between different models or algorithms used for skin lesion classification. The comparison helps in selecting the most effective model based on various performance metrics and criteria.

5. CONCLUSION

In conclusion, the project presents a robust system for the detection of melanoma and non-melanoma skin lesions from dermoscopic images. By integrating traditional machine learning techniques like Gaussian Naive Bayes Classifier (GNB) with deep learning methods such as Convolutional Neural Networks (CNN), the system achieves accurate classification results. The GUI interface enhances user interaction and makes the system accessible to medical practitioners and researchers.

The implemented models demonstrate promising performance in classifying dermoscopic images, as evidenced by the evaluation metrics and visualized confusion matrices. The comparison between the GNB classifier and the CNN model provides valuable insights into the efficacy of different approaches for lesion classification.

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