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AN AUTOMATED AND ARTIFICIAL INTELLIGENCE-BASED SYSTEM FOR THE DIAGNOSIS OF SKIN CANCER

Syeda Qanitah Naqvi[1], Syeda Rabail Zahra[2], Muhammad Sajid Maqbool[*3], Muqadas Nadeem[4], Hira Saleem[*5], Mahnoor Zaman[6]

[1]*Department of Software Engineering, National University of Modern Languages, Multan*
[2]*Department of Computer and Software Engineering, Faculty of Computing, Gomal University, Dera Ismail Khan*
[*3,*5,6]*Department of Computer Science, NFC Institute of Engineering and Technology, Multan*
[4]*Department of Computer Science, Emerson University, Multan, Pakistan*

[1]qanitah.naqvi@numl.edu.pk, [2]rabail@gu.edu.pk, [*3]sajid.maqbool@nfciet.edu.pk,
[4]nmuqadas587@gmail.com, [*5]hira.saleem@nfciet.edu.pk, [6]786mahnoorzaman@gmail.com

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Corresponding Author: *
Muhammad Sajid Maqbool, Hira Saleem

Abstract

Skin cancer is one of the most prevalent and potentially life-threatening diseases worldwide, where early and accurate diagnosis plays a critical role in improving patient survival rates. This study presents a deep learning-based framework for the automated classification of skin cancer using thermoscopic images.
The proposed methodology consists of a systematic pipeline including image preprocessing, dataset preparation, model development, and performance evaluation. A publicly available dataset comprising 3304 images is utilized, which is divided into training and testing subsets. Various preprocessing techniques such as resizing, normalization, equalization, and data augmentation are applied to enhance image quality, reduce overfitting, and improve model generalization. To perform classification, two advanced Convolutional Neural Network architectures, ResNet101 and ResNet152, are employed due to their ability to learn complex visual features through residual learning. The models are trained using optimized hyperparameters, including appropriate learning rates, batch sizes, and epochs, to achieve efficient convergence and high performance. The experimental results demonstrate that both models achieve outstanding performance, with 100% training accuracy. ResNet101 attains a testing accuracy of 98.35%, while ResNet152 outperforms with a testing accuracy of 99.15%, along with minimal loss values, indicating strong generalization and robustness. A comparative analysis highlights the superior performance of the deeper ResNet152 model in accurately distinguishing between benign and malignant skin lesions. The findings suggest that the proposed framework is highly effective for early detection of skin cancer and has strong potential for integration into computer-aided diagnostic systems. This work contributes to the advancement of automated medical image analysis and supports the development of reliable and efficient tools for clinical decision-making.

1 INTRODUCTION

Skin cancer is a substantial public health alarm, with early detection being vital for actual treatment and improved patient outcomes. In this research, we are exploring the application of deep learning techniques for automated disclosure and classification of skin cancer using thermoscope images. The aim of this research to develop a full-bodied and accurate deep learning model that can support dermatologists in diagnosing skin cancer. We begin by curating an all-inclusive dataset comprising thermoscope images of two types of skin Cancers, including malignant and benign Cancers. Deep learning architectures, such as convolutional neural networks, provide hypotheses in which a multi-class classification model is capable of distinguishing between different Cancer categories. To address the limitations linked with data scarcity and model complexity, we employ techniques such as data augmentation and transfer learning. Through wide-ranging experimentation, we enhance the model's hyperparameters and its performance by using metrics such as accuracy, sensitivity, and specificity. We compare the performance of a deep learning model against old machine learning methods and assess its dermatologist-level accuracy. However, we acknowledge several limitations in our study. The availability of diverse and well-annotated meatoscopic images remains a challenge, potentially impacting the model's generalization ability. Furthermore, while the deep learning model can provide treasured insights, its decision-making process lacks transparency, demanding the involvement of clinical experts for informed decisions. In conclusion, this thesis contributes to the advancement of automated skin cancer detection using deep learning techniques. Our findings recommend that the proposed model demonstrates more accuracy and they have budding to assist dermatologists in making informed diagnoses. We highlight the importance of a collaborative approach, where the deep learning model complements clinical expertise for enhanced patient care. Future work may involve refining the model's interpretability, incorporating additional data sources, and addressing ethical deliberations to ensure responsible and effective deployment.

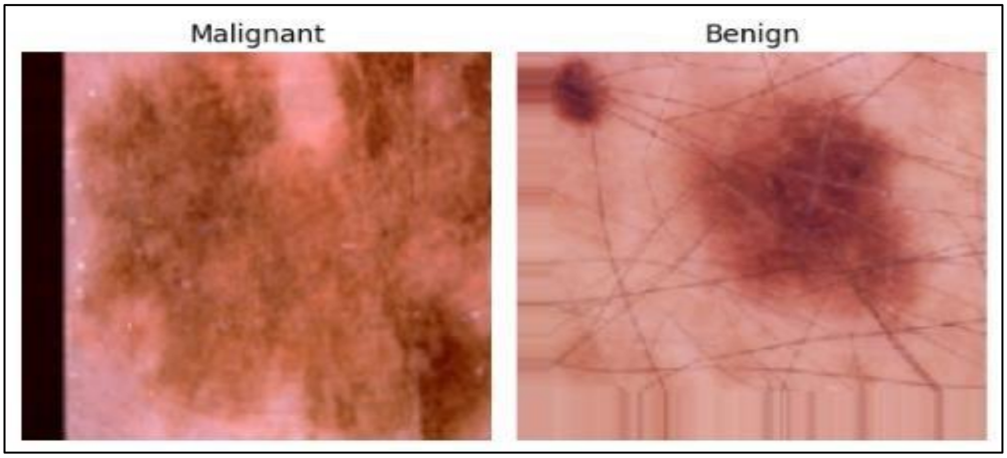

Figure 1 Sample images of skin cancer

Skin cancer is the most common type of cancer globally, with its occurrence regularly growing during the last few decades. It touches individuals of all centuries, genders, and cultural backgrounds, posing a significant fitness burden on societies. Early detection and correct analysis of pores and Skin cancer are key to effective remedy and improved patient outcomes.

However, the visible valuation of skin Cancers by dermatologists may be stimulating and subjective, leading to diagnostic imprecision and delayed interventions. Skin cancer is a chief global health problem, with fees step by step growing in recent years (Codella et al., 20124). . According to the World Health Organization (WHO), Skin cancer accounts for around one-third of all cancer diagnoses internationally, with an envisioned 2 to 3 million non-cancerous skin cancers and 132,000 cancerous skin cancers identified every year. Early detection and particular analysis are crucial for successful therapy and better patient results. However, dermatologists' visual evaluation of skin Cancers, which is the modern-day diagnostic gold standard, can be subjective and error-prone. Recent advances in AI and deep learning have shown promising consequences in several scientific imaging applications, such as the identification and categorization of skin cancer. Deep gaining knowledge of fashions, together with Dense Net variations and Inception-V3, has proven superb performance in picture recognition assessments, making them best for analyzing skin Cancer images (Codella et al., 20124). The purpose of this thesis is to explore the efficacy of the Dense Net variant and Inception-V3 fashions for the pores and Skin cancer category using clinical snapshots. The study will use a massive dataset of pores and skin Cancer images received from numerous clinical records and publicly available datasets. To ensure the dataset is great, preprocessing strategies might be used to improve the pictures and prepare them for input into deep learning models. Dense Net version and Inception-V3 fashions were chosen for their architectural functions, which have been verified to be beneficial in picture classification tasks (Tschandl et al., 2025). . Dense Net, with its dense connectivity architecture, allows function reuse throughout layers, resulting in efficient learning and parameter reduction. Inception-V3, however, is aimed at seizing multi-scale capabilities whilst additionally preventing the vanishing gradient trouble. The objectives of this study are:

- To collect a dataset of skin cancer from different medical repositories and an online dataset repository.
- To implement state-of-the-art deep learning constructions for skin cancer detection, such as CNN models.
- To preprocess the collected dataset and then use the constructed dataset to train and fine-tune deep learning models, prioritizing high accuracy in both training and testing.

2 Literature Review

In the field of pores and skin cancer reputation the usage of deep learning, several theories and judgments were advanced to improve the accuracy and competency of detection algorithms. These theories function as the foundation for the introduction and implementation of DL fashions in skin cancer analysis. Some of the associated theories are given in this bankruptcy.

Convolutional Neural Networks (CNNs) have established first-rate performance in image interpretation and pattern recognition applications. CNNs use convolutional sheets to extract functions hierarchically from input images, followed by fully connected layers for the category. CNNs have gained a reputation in skin cancer prognosis because of their ability to robotically examine and represent multidimensional factors from meatoscopic photographs, making allowance for the correct identification of malignant skin Cancers. Transfer Learning (DL) is a method that lets pre-trained deep studying fashions to function a place to begin for practice on a new project. Transfer learning aids in the identification of skin cancer via the use of data from a large dataset. It allows the transfer of found topographies from fashions skilled on comparable photograph datasets, as a result, boosting the overall performance and simplification of Skin cancer detection simulations. Data Augmentation (DA) is a technique that aims to artificially grow the schooling dataset by applying numerous alterations and modifications to present photographs. This method addresses the uneven accessibility of categorized meatoscopic photos even as decreasing overfitting in deep mastering fashions. Spin, scaling, flipping, and picture noise addition are all examples of mutual information augmentation techniques. In the era of skin cancer diagnosis, the usage of deep learning has been explored in several studies to analyze loads of policies and techniques. These investigations contributed to the development of improved strategies and fashions. Some brilliant efforts on this subject consist of:

Skin cancer is a severe public health problem, with melanoma being the most common type and accounting for the majority of skin cancer-related deaths (Miller et al., 2019). Early detection is crucial for successful remedy, emphasizing the importance of unique and efficient diagnostic techniques. Traditional skin cancer detection is predicated on dermatologists' visual inspections, which may be subjective and result in misdiagnosis (Tschandl et al., 2025). Recent advances in AI and DL have confirmed the promise in enhancing the accuracy and performance of Skin cancer diagnosis through the use of scientific photo analysis. Deep getting to know models, which include CNN, have proven staggering performance in picture-primarily based categorization tasks, consisting of pores and skin cancer diagnosis (Esteva et al., 2017). One of the most massive problems in Skin cancer type is the necessity for large and numerous datasets to teach deep getting to know fashions. The International Skin Imaging Collaboration (ISIC) has made important contributions to this area via preserving the ISIC Archive, a dataset of pores and skin Cancer pics that has been utilized in numerous research to teach and evaluate deep learning models (Codella et al., 20124). Dense-Net, a CNN version, has proven capability in picture category duties by way of encouraging feature reuse via dense connectivity across layers (Huang et al., 2017). This allows the version to accumulate extra discriminative characteristics from the entire, doubtlessly enhancing accuracy in skin cancer categorization tasks. Similarly, the Inception-V3 version, superb for its inception modules and auxiliary classifiers, is typically used for picture classification (Szegedy et al., 2016). Inception-V3's capacity to capture multi-scale functions makes it best for comparing pores and skin Cancer photographs, which often contain complicated styles and textures. Preprocessing strategies are crucial in making ready the dataset for schooling deep studying models. Image normalization, standardization, and information augmentation are outstanding techniques used to enhance dataset fine-tuning and variety, which leads to better version performance (Krizhevsky et al., 2022). Several studies have proven that deep learning knowledge of fashions, which include DenseNet versions and Inception-V3, can correctly classify skin cancer. Esteva et al. (2017) used a CNN version trained on a dataset of skin Cancer photographs from the ISIC Archive to acquire high accuracy in figuring out malignant and benign Cancers. In a comparable study, Tschandl et al. (2018) assessed the effectiveness of numerous deep learning models, including DenseNet, in classifying skin Cancers. They found that DenseNet outperformed different fashions in terms of accuracy and sensitivity, indicating its capacity for therapeutic use. Furthermore, Haenssle et al. (2018) tested a deep mastering set of rules' ability to classify pores and skin Cancers the usage of a dataset of photographs amassed from dermatology clinics. They pronounced notable sensitivity and specificity, highlighting the ability of deep learning algorithms to assist dermatologists in diagnosing skin cancer. To summarize, the application of deep learning fashions, along with the DenseNet version and Inception-V3, indicates tremendous promise for boosting the accuracy and performance of Skin cancer type. When trained on huge and numerous datasets, these fashions can help dermatologists diagnose skin cancer more appropriately and enhance patient outcomes.

Table 1 Comparison of Papers Results

Authors	Year	Dataset	Classes	Technique	Accuracy
Asmaa Abbas et al	2025	Dermoscopic images	Binary	Deep Learning	93%
Sarwan Ali and Murray Patterson	2024	Genomic Data	Binary	Deep Learning and Machine Learning	93%
Khandaker Foysal Haque and Ahmed Abdelgawad	2024	chest X-ray	Binary	Deep CNN	96%
Joy Iong-Zong Chen et al.	2023	Dermoscopic images	Binary	HOG CNN	89%
Samira Chamyani et al	2025	Dermoscopic images	Binary	CNN	91%
Ravneet Punia et al.	2025	Radiology and X-Ray	Binary	ResNet	91%
A.E. Fughes et al.	2022	chest X-ray	Multi	SVM and CNN	90%
Mustafa Akyol et al.	2022	Heart X-ray	Binary	CNN	89%
Hongtao Xie et al.	2023	Dermoscopic images	Multi	CNN	86%
L.G. Wang Chen et al.	2024	Dermoscopic images	Binary	CNN	78%
Radhakrishnan Srinivasan et al.	2024	Dermoscopic images	Multi	GMM	90%
L. Shen et al.	2020	X-Ray	Binary	CNN Deep Net	90.4%
U. Khasana et.al	2019	CNN	Binary	CNN	92.5%

3 Materials and Methods

The methodology proposed in the study for skin cancer detection using deep learning is structured into three integrated phases that collectively ensure accurate and reliable classification of skin cancer, as shown in Figure 3. In the first phase, a publicly available dataset of skin Cancer images is acquired from Kaggle and undergoes extensive preprocessing to enhance data quality and suitability for model training; this includes resizing all images to a uniform dimension for consistency, normalizing image values to stabilize and accelerate the learning process, and applying data augmentation techniques such as rotation, flipping, and zooming to artificially expand the dataset, reduce overfitting, and improve the model's ability to generalize to unseen data, followed by splitting the dataset into training and testing subsets to enable proper performance evaluation. In the second phase, the study focuses on model development, where multiple deep learning approaches are explored, with primary emphasis on designing a customized Convolutional Neural Networks (Resnet 101 and 152) architecture tailored specifically for skin cancer classification; this CNN is responsible for automatically extracting meaningful and discriminative features from images, such as texture, color variations, and structural patterns, and using them to perform classification, while key hyperparameters including learning rate, batch size, and number of training epochs are carefully tuned to optimize the model's efficiency, convergence speed, and overall generalization capability.

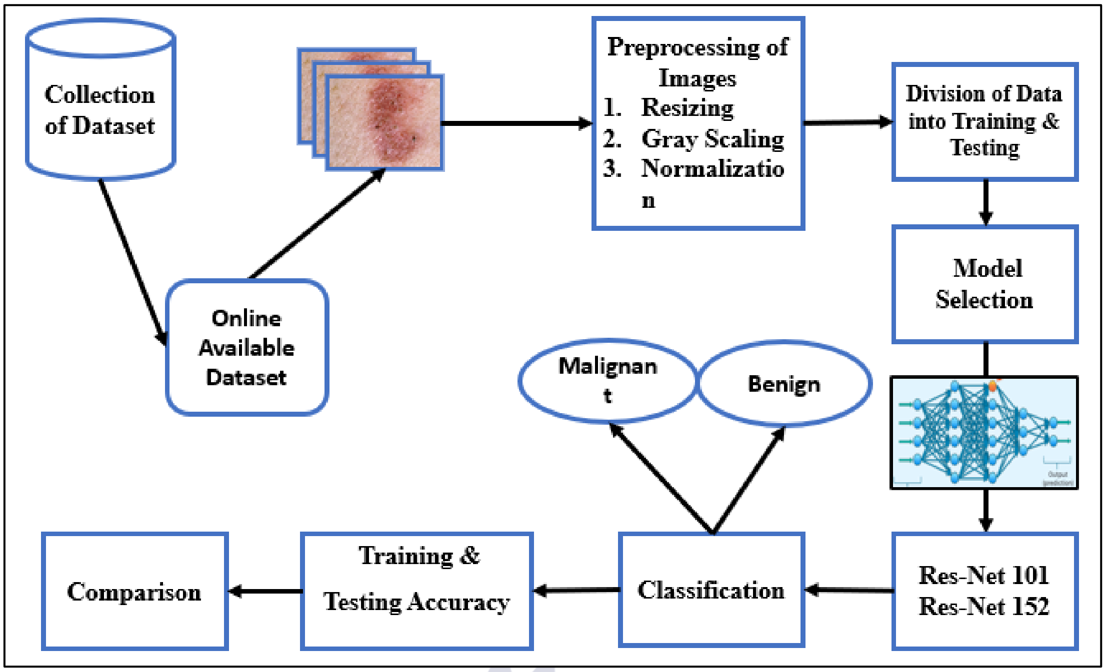

Figure 2 Proposed Framework

In the third and final phase, the trained model is employed to classify images into cancerous and non-cancerous categories, and its performance is rigorously evaluated using standard metrics such as training accuracy, testing accuracy, and loss values, followed by a comparative analysis with existing state-of-the-art models to validate its effectiveness, where the experimental results demonstrate that the proposed approach achieves superior performance, notably reaching a high testing accuracy of 99% along with reduced loss, thereby indicating that the model is both robust and reliable for early detection of skin cancer.

3.1 Preprocessing of images

Preprocessing of images in DL includes a chain of steps to prepare uncooked picture facts to be used in training deep learning models. Proper preprocessing is vital for improving the performance and accuracy of deep learning models. Here are the key preprocessing steps that are used in our proposed methodology:

- Resizing
- Scaling/Green Channeling
- Equalization
- Normalization
- Augmentation

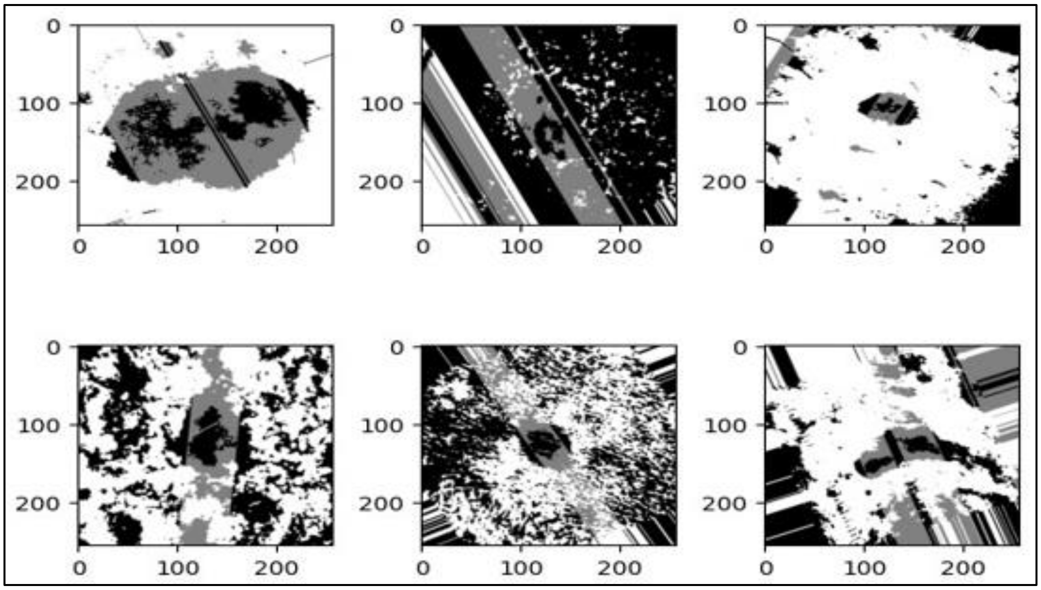

Figure 3 Sample of Images after applying all preprocessing steps

3.2 Division of the Dataset

Our selected dataset contains a total of 3304 images, which are divided into training and testing. Table 2 presents a clear breakdown of the dataset into training and testing subsets. Out of a total of 3304 pictures, 2647 are allotted for training functions, at the same time as the last remaining 660 images are targeted for testing. This division is vital for constructing a sturdy deep learning model, as it guarantees that the version has a widespread quantity of records to research from (the training set) and a separate set of records (the testing set) to validate its overall performance. By segregating the facts in this manner, the version may be trained effectively, after which it may be examined on unseen data to gauge its accuracy and generalization capability.

Table 2 Division of Images

Dataset	Counting
Training Images	2647
Testing Images	660
Total	3304

Table 3 details the distribution of images across classes—Benign and Malignant—for both the train and test datasets. In the training set, there are 1450 Benign photographs and 1197 Malignant photos, imparting a balanced dataset for the version to research from. For training the model, there are 360 Benign pictures and 300 Malignant pictures, ensuring that the assessment of the model includes a truthful illustration of both classes. Overall, the dataset comprises 1810 Benign pics and 1497 Malignant photographs.

Table 3 Class-wise Distribution

Class	Benign	Malignant
Training	1450	1197
Testing	360	300
Total	1810	1497

This distribution is important for training the CNN model to correctly differentiate between diseased and normal conditions of skin cancer, and for testing the model to ensure it performs well across both categories.

3.2.1 Creating a Deep Learning Model

We use two different versions of the ResNet model (101 and 152) to evaluate our proposed methodology.

3.2.1.1 Res-Net101

ResNet101 is a deep convolutional neural network (CNN) architecture that is part of the ResNet (Residual Networks) family. Res-Net architectures are widely recognized for their innovative method to training very deep networks by means of introducing residual connections, which help mitigate the vanishing gradient trouble and permit the training of an awful lot of deeper networks.

3.2.1.2 Res-Net 152

ResNet-152 is one of the deeper models within the Residual Network (ResNet) family, which is known for its depth and overall performance on image classification tasks. It consists of 152 layers and makes use of the residual learning framework to ease the training of very deep networks. Here's an overview of ResNet-152, consisting of its architecture and implementation examples. Key Features of ResNet-152 Depth: ResNet152 has 152 layers, making it one of the private fashions within the ResNet family.

3.3 Classifying and Evaluating

We evaluate our proposed model based on the following parameters:

- Training Accuracy
- Testing Accuracy
- Training Loss
- Testing Loss

4 Results and Evaluations

This section offers an outline of the overall performance of both CNN models, ResNet101 and ResNet152. The consequences of training and comparing those models on our processed dataset. For each model, we set key metrics including training and testing at losses, in addition to accuracy rankings. We compare how the two architectures finished, highlighting differences in their ability to generalize and their effectiveness in classifying the records. The consequences exhibit the model's strengths and offer insights into their comparative overall performance, putting the degree for a deeper analysis in their effectiveness and implications in the subsequent section.
Table 4 explains the configuration details for the Res-Net 101 and 152 models used inside the experiments. The details of the tables are:

Table 4 Architecture of Used CNN Models

Parameter	**Detail**
No of Epochs	10
Batch Size	256/128
Optimizer	Adam
Learning Rate	0.001/0.01
Loss	Binary loss
Activation Functions	Pretrained Models
System	GPU

Table 4.3 displays the loss values for the ResNet101 model for the duration of training and testing. The training loss is distinctly low at 0.002, reflecting the model's excessive accuracy and effective getting to know on the training dataset. In evaluation, the test loss is barely better at 0.015, which is expected and shows that the model's overall performance on unseen information is also quite robust. The small gap between the train and test loss shows that the model generalizes nicely without overfitting, preserving a low stage of prediction errors across each dataset.

Table 5 ResNet101 Loss

Loss	**Value**
Train	0.002
Test	0.015

Table 6 gives the accuracy metrics for the ResNet101 model, displaying a training accuracy of 100% and a testing accuracy of 98.35%. Table 6 ResNet101 Accuracy

Accuracy	**Value**
Train	100
Test	98.35

The ideal train accuracy shows that the version has discovered to classify the training information flawlessly, whilst the high testing at accuracy demonstrates excellent generalization to new, unseen statistics. The proximity of the training and testing at accuracies highlights the version's robustness and effectiveness in each acquainted and novel scenario, underscoring its functionality to perform well across exclusive fact sets.

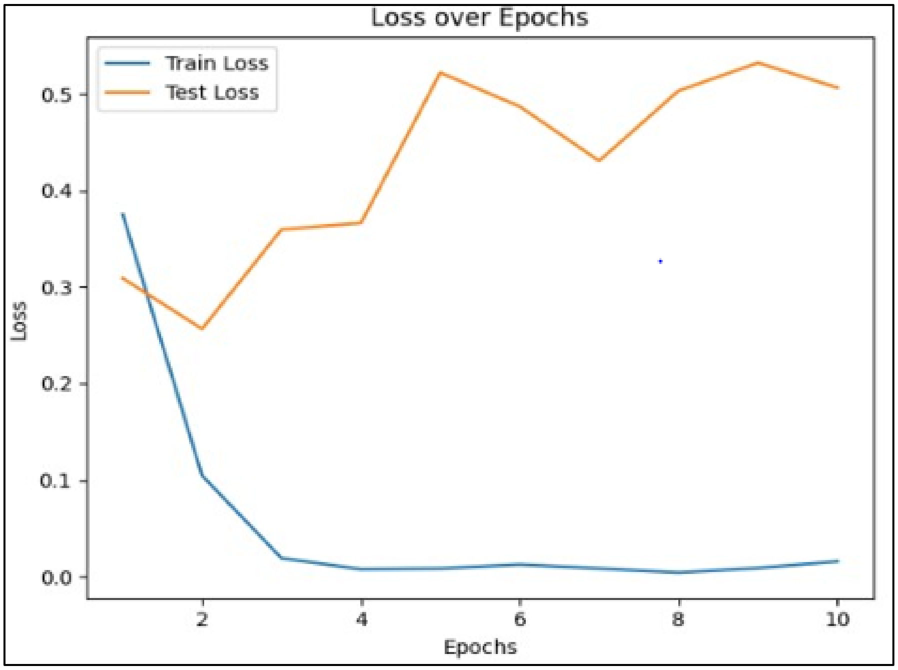

Figure 4 Loss Graph of ResNet101

Figure 4 shows the Training and Testing loss of the ResNet101 model. The loss of the model is low at epoch 1, and it gradually increases as the epoch increases. This means that our model is trained well and performs better on the training dataset. The X-axis of the graph shows the number of epochs, which starts from 1 to 10 because we have 10 epochs for our ResNet101. The y-axis of the graph shows the loss value of the models. The graph contains two colors of lines: blue indicates the training loss, and orange indicates the testing loss.

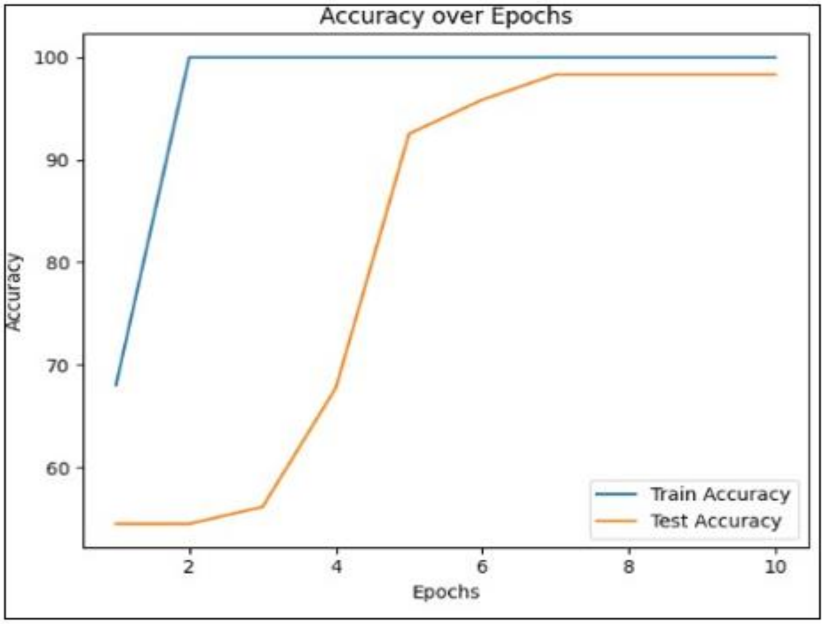

Figure 5 Accuracy Graph of ResNet101

Figure 5 shows the Training and Testing accuracy of the ResNet101 model. The accuracy of the model is low at epoch 1, and it gradually increases as the epoch increases. This means that our model is trained well and performs better on the training dataset. The X-axis of the graph shows the number of epochs, which starts from 1 to 10 because we have 10 epochs for our ResNet101. The y-axis of the graph shows the accuracy value of the models. The graph contains two colors of lines: blue indicates the training accuracy, and orange indicates the testing accuracy.

Table 7 ResNet152 Loss

Loss	Value
Train	0.02
Test	0.001

Table 8 provides the accuracy metrics for the ResNet152 model on both training and test datasets. The training accuracy is reported as 100%, demonstrating that the model achieved perfect classification on the training data. The test accuracy is slightly lower at 99.15%, which, while still very high, indicates a small drop in performance when applied to unseen data. The high-test accuracy confirms that the model generalizes well to new data, though the slight reduction compared to training accuracy suggests there may be minor generalization challenges or differences between the training and test datasets.

Table 8 ResNet152 Accuracy

Accuracy	Value
Train	100
Test	99.15

Figure 4.3 shows the Training and Testing loss of ResNet152 model. The loss of model is low at the epoch 1 and it gradually increases as the epoch is increases it means that our model is trained well and perform better on the training dataset. X-axis of the graph shows the number of epochs that starts from 1 to 10 because we 10 epochs for our ResNet101. Yaxis of the graph shows the loss value of the models. The graph contains two colors of lines blue color indicate the training loss and orange color indicates the testing loss.

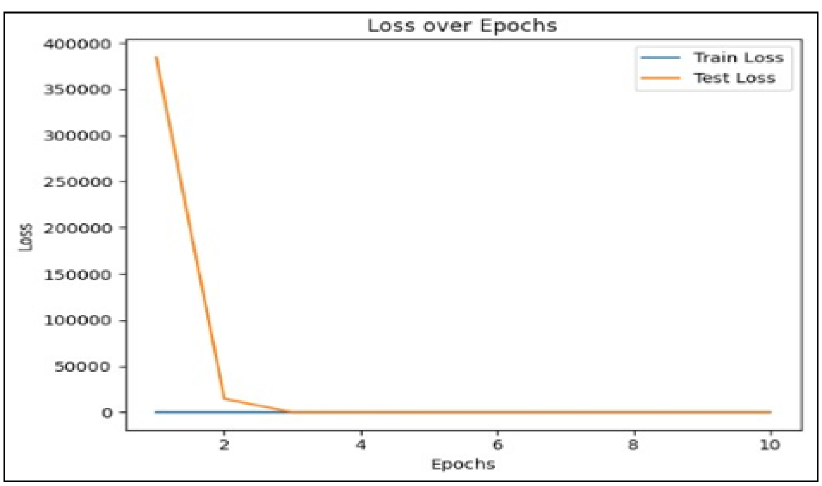

Figure 6 Loss Graph of ResNet152

Figure 6 shows the Training and Testing accuracy of ResNet152 model. The accuracy of the model is low at epoch 1, and it gradually increases as the epoch increases. This means that our model is trained well and performs better on the training dataset. The X-axis of the graph shows the number of epochs, which starts from 1 to 10 because we have 10 epochs for our ResNet101. The y-axis of the graph shows the accuracy value of the models. The graph contains two colors of lines: blue indicates the training accuracy, and orange indicates the testing accuracy.

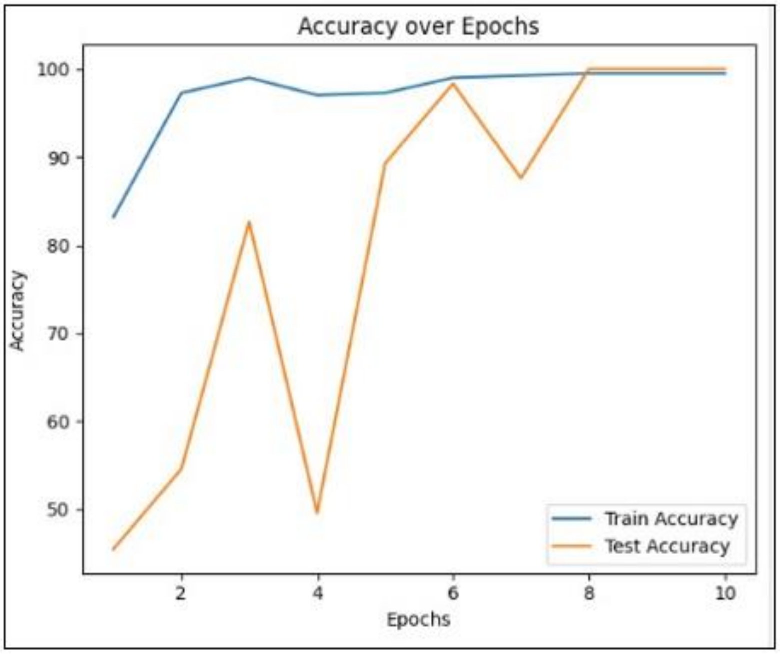

Figure 7 Accuracy of Res-Net 152

5 Conclusion

In this study, a deep learning-based framework was successfully developed for the accurate classification of skin cancer using thermoscopic images. The proposed methodology incorporated a well-structured pipeline consisting of data preprocessing, dataset division, model development using advanced Convolutional Neural Network architectures (ResNet101 and ResNet152), and comprehensive evaluation using standard performance metrics. The preprocessing techniques, including resizing, normalization, equalization, and data augmentation, significantly enhanced the quality and diversity of the dataset, enabling the models to learn more robust and discriminative features. The balanced distribution of benign and malignant classes further contributed to effective model training and unbiased evaluation.

Two deep residual network models, ResNet101 and ResNet152, were implemented and compared to assess their performance in skin cancer classification. Both models demonstrated exceptional results, achieving perfect training accuracy (100%) and very high testing accuracy, with ResNet101 reaching 98.35% and ResNet152 achieving an improved accuracy of 99.15%. Additionally, the loss values for both models remained minimal, indicating stable learning and strong generalization capability with negligible overfitting. Among the two, ResNet152 slightly outperformed ResNet101 in terms of testing accuracy and overall reliability, highlighting the advantage of deeper architectures in capturing complex patterns within medical images. Overall, the experimental results confirm that the proposed deep learning framework is highly effective and reliable for early detection and classification of skin cancer. The high accuracy and low loss values demonstrate the model's robustness and its potential applicability in real-world clinical decision support systems. This approach can assist healthcare professionals in making faster and more accurate diagnoses, ultimately improving patient outcomes. Future work may focus on expanding the dataset, incorporating multi-class classification, and integrating the model into practical medical applications for broader clinical use.

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