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A MULTI-CLASS SKIN CANCER CLASSIFICATION USING OPTIMIZED CNN FOR DEEP SKIN HEALTHCARE SYSTEM

1 Alle Shiva Sai, University College of Engineering, Science and Technology, JNTUH Hyderabad
2 Dr. M Dhanalakshmi, Professor of IT, University College of Engineering, Science and Technology, JNTUH Hyderabad

Abstract: Skin cancer is the most common type of cancer worldwide, and early and precise detection is important for patient survival. Clinical examination of skin lesions is critical, but it is fraught with difficulties such as extended wait times and subjective interpretations. Every year, around a million people are diagnosed with the condition in India alone. As the disease advances, the rate of survival falls drastically. To address these issues and assist dermatologists in making more accurate diagnoses, deep learning algorithms have been created. Deep learning algorithms can enhance diagnosis speed and accuracy, resulting in early detection and treatment. This study's objective was to develop strong deep learning (DL) prediction models for the categorization of skin cancer by first addressing a common severe class imbalance problem and other preprocessing work, then building an improved model for prediction, and finally proposing an end-to-end smart healthcare system via a web application. We tackle this issue by utilizing ISIC's HAM10000 dataset. It comprises 10015+ dermoscopic images that are freely available to the public. In this study, we will use convolutional neural networks (CNN) to detect and categorize seven different types of skin cancer using historical clinical imaging data. Building an optimized CNN model to accurately diagnose skin cancer, lowering the false negative prediction rate, and performing data visualization are some of our main goals for this study. The study will demonstrate how CNNs have the capacity to accurately categorize various skin cancers, which can aid in the detection and improvement of a patient's prognosis.

Index Terms: *Skin Cancer, Deep Learning, CNN, Smart Healthcare System, Multi-class Skin Cancer Classification*

1. INTRODUCTION

The skin is one of the body's most extensive organ systems, playing a pivotal role in regulating body temperature and providing protection against excessive heat and sunlight [1]. Additionally, it serves as a reservoir for fat and water. Skin cancer originates from the skin cells, the fundamental building blocks of the skin. These cells proliferate and divide to create new ones, undergoing a natural process of aging and death, with new cells replacing them at various points. Occasionally, this orderly process falters, leading to the accumulation of new cells when they are not needed and the persistence of old cells that should have died. This malfunction can lead to the development of skin cancer.

Skin cancer is a significant global health issue, causing numerous fatalities each year [2]. Annually, approximately 5.4 million new cases are identified, marking it as a substantial public health concern [3]. In recent years, the incidence of skin cancer has surged, particularly in countries like the United States, Australia, and Canada. Over 15,000 people die annually due to skin cancer, with specific subtypes posing significant mortality risks. For instance, in 2021, a single subtype of skin cancer claimed the lives of 7,180 people in the United States alone, with projections indicating that 7,650 individuals will succumb to melanoma in 2022 [4].

Among the various categories of skin cancer, melanoma stands out as the most common and dangerous form, responsible for a higher death toll compared to other types. The exact causes of melanoma remain elusive, but it is believed to be influenced by genetic factors and exposure to ultraviolet (UV) rays. Despite the high mortality rate associated with melanoma, early detection can significantly improve survival rates, with the five-year survival rate reaching up to 99% if diagnosed early [5].

Dermatologists play a crucial role in diagnosing skin cancer, often relying on clinical examinations to assess skin lesion characteristics such as color, texture, and shape. This assessment involves both physical analysis and the application of clinical expertise. However, access to dermatologists can be limited due to their high demand and associated costs, which poses a barrier to timely diagnosis and treatment. Early identification and diagnosis are critical for improving patient outcomes and reducing morbidity and mortality associated with skin cancer [3].

Automated tools that leverage deep learning algorithms, particularly convolutional neural networks (CNNs), offer a promising solution to these challenges. CNNs are well-suited for image classification tasks due to their ability to automatically learn features from raw data. This capability makes them an ideal choice for tasks involving the classification of medical images, including skin lesions.

In this project, we introduce a comprehensive approach to pre-processing and segmenting skin lesions, extracting relevant features from these segments, and training a machine learning model to accurately categorize the lesions. We utilize an enhanced CNN on the HAM10000 dataset, which comprises over 10,015 dermoscopic images, to identify seven specific types of skin lesions: melanocytic nevi, vascular lesions, benign keratosis-like lesions, basal cell carcinoma, melanoma, actinic keratoses, and dermatofibroma. Our methodology includes extensive training to address the common issue of imbalanced datasets, which can adversely affect model accuracy.

To tackle the class imbalance problem, we implement various techniques such as data augmentation, re-sampling, and the use of weighted loss functions. These techniques help to ensure that the model does not become biased towards the majority class, thereby improving its overall performance. Additionally, we employ advanced data visualization tools to provide insights into the model's learning process and to highlight the distinguishing features of different skin lesion types.

Our study demonstrates the effectiveness of CNNs in accurately classifying various skin cancers, thereby aiding in early detection and improving patient prognosis. The proposed end-to-end smart healthcare system, implemented via a web application, facilitates these advancements by providing dermatologists with a reliable tool for making more accurate diagnoses. This integration of deep learning technology into clinical practice represents a significant step forward in the fight against skin cancer, offering the potential to save countless lives through early and precise detection.

In conclusion, our research presents a robust deep learning model with enhanced accuracy for skin cancer classification. By addressing the challenges of class imbalance and leveraging the power of CNNs, we provide a valuable tool for dermatologists, ultimately contributing to improved patient outcomes and a reduction in skin cancer-related mortality.

2. LITERATURE SURVEY

The increasing prevalence of skin cancer, particularly melanoma, necessitates the development of reliable diagnostic tools to aid early detection and improve patient outcomes. Traditional diagnostic methods involve dermatologists' visual assessments of skin lesions, which can be subjective and time-consuming. Recent advances in deep learning, especially convolutional neural networks (CNNs), offer promising alternatives for automated and accurate skin cancer classification.

Traditional methods for diagnosing skin cancer rely heavily on dermatologists' clinical expertise to evaluate skin lesions based on their visual characteristics such as color, texture, and shape. This process is not only subjective but also limited by the availability and accessibility of skilled dermatologists [1]. Furthermore, with the rising number of skin cancer cases globally, there is an urgent need for efficient diagnostic tools to reduce the burden on healthcare systems and provide timely interventions.

Deep learning techniques, particularly CNNs, have shown remarkable success in image classification tasks, including medical image analysis. CNNs can automatically learn hierarchical features from raw image data, making them suitable for detecting and classifying skin lesions. Several studies have demonstrated the effectiveness of CNNs in improving the accuracy and efficiency of skin cancer diagnosis.

Gouda et al. [6] explored the use of deep learning for skin cancer detection by leveraging skin lesion images. Their study highlighted the potential of CNNs to identify various skin cancer types with high accuracy. They utilized a dataset of skin lesion images and trained a CNN model to distinguish between different categories of skin lesions. The results indicated that deep learning could significantly enhance diagnostic precision.

Similarly, Fu'adah et al. [7] developed an automatic skin cancer classification system using CNNs. Their research focused on building a CNN model capable of categorizing skin lesions into benign and malignant types. By employing a large dataset and extensive data augmentation techniques, they achieved notable accuracy, underscoring the robustness of CNNs in handling complex image classification tasks.

Dorj et al. [8] proposed a deep convolutional neural network for skin cancer classification, emphasizing the model's ability to learn from dermoscopic images. Their approach demonstrated high classification accuracy and reduced the need for manual feature extraction. This study reinforced the potential of deep learning models to outperform traditional diagnostic methods in terms of speed and accuracy.

One of the primary challenges in developing effective deep learning models for skin cancer classification is the issue of class imbalance. Skin cancer datasets often contain a disproportionate number of images from different classes, which can bias the model towards the majority class and degrade performance on minority classes. Several studies have addressed this issue using various techniques.

Subramanian et al. [9] tackled the class imbalance problem by employing data augmentation and re-sampling methods. Their study involved creating synthetic samples for underrepresented classes and adjusting the model's training process to ensure balanced learning. This approach significantly improved the model's performance, particularly for rare classes.

Mridha et al. [10] focused on optimizing CNN architectures to enhance interpretability and accuracy. They proposed a novel CNN model designed to provide interpretable results, aiding clinicians in understanding the model's predictions. Their work highlighted the importance of model transparency in clinical applications, ensuring that the AI system's decisions are understandable and trustworthy.

Transfer learning, which involves leveraging pre-trained models on large datasets, has also been explored to improve skin cancer classification. Hosny et al. [11] investigated the use of transfer learning for skin cancer detection, demonstrating that pre-trained models could significantly enhance classification performance, particularly when dealing with limited datasets. Their findings suggested that transfer learning could be a valuable strategy for developing robust and accurate skin cancer detection systems.

The literature underscores the potential of deep learning, particularly CNNs, in revolutionizing skin cancer diagnosis. Studies have consistently shown that CNNs can achieve high accuracy in classifying skin lesions, addressing the limitations of traditional diagnostic methods. Techniques such as data augmentation, re-sampling, and transfer learning further enhance the robustness and reliability of these models. As research progresses, integrating deep learning models into clinical practice could significantly improve early detection and treatment of skin cancer, ultimately saving lives.

3. METHODOLOGY

a) Proposed Work:

The proposed work involves the development of a comprehensive system for skin cancer detection using deep learning. Initially, we gather a diverse and extensive dataset encompassing various skin lesion images, ensuring representation across different skin types and lesion types. This approach addresses issues of limited dataset size and data imbalance. Robust image preprocessing techniques are employed to standardize image quality and reduce noise, ensuring consistency across the dataset.

Our system is built around a convolutional neural network (CNN) architecture, designed to process image pixels through multiple layers to accurately predict skin cancer. The CNN model undergoes extensive training, and we employ comprehensive evaluation metrics, including accuracy, precision, recall, and F1-score, to ensure robust model performance.

To enhance usability, we integrate the developed model into a user-friendly interface or decision support system. This system provides real-time skin cancer classification predictions and interpretability insights, aiding medical practitioners in early detection and accurate diagnosis. By combining advanced deep learning techniques with practical application tools, our proposed work aims to significantly improve the accuracy and efficiency of skin cancer detection, ultimately contributing to better patient outcomes.

b) System Architecture:

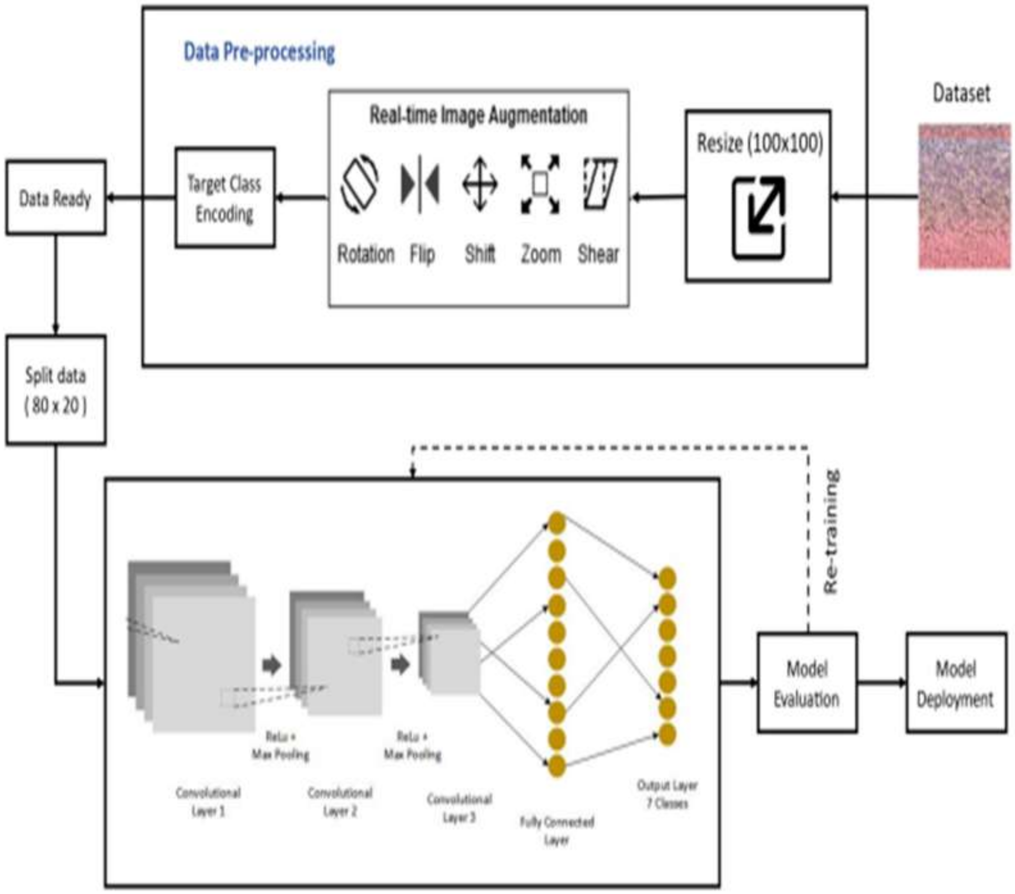

Fig 1 Proposed Architecture

The Deep Skin Healthcare System is a self-automated tool designed for the identification of skin cancer types, structured in a multi-phase architecture. Initially, data preparation involves gathering a diverse set of skin lesion images, ensuring representation across various skin and lesion types, and applying robust preprocessing techniques to standardize image quality and reduce noise. The training phase utilizes a convolutional neural network (CNN) architecture, where the preprocessed images are fed into the model, which learns to classify different types of skin cancer through multiple layers. Comprehensive evaluation metrics, including accuracy, precision, recall, and F1-score, guide the training process to ensure robust performance. Finally, the deployment phase integrates the trained model into a user-friendly interface or decision support system, enabling real-time skin cancer classification predictions. This system also provides interpretability insights to assist medical practitioners in making informed decisions, facilitating early detection and accurate diagnosis.

c) Dataset Collection:

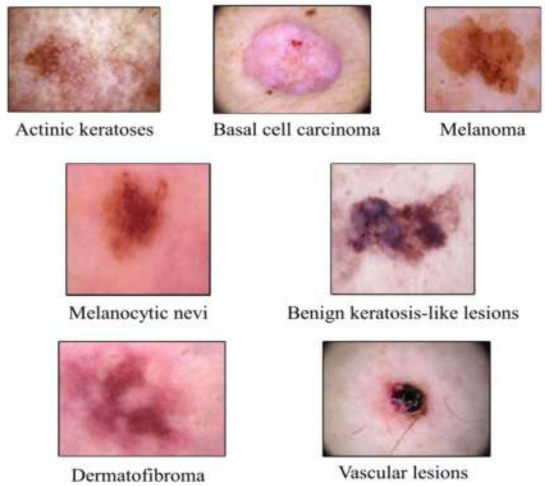

Fig 2 Dataset

The dataset collection process for this study involved obtaining two primary datasets: HAM10000 (Human Against Machine) and the dataset from the International Skin Imaging Collaboration (ISIC). The HAM10000 dataset comprises 10,000 training images and an additional 15 images, totaling 10,015 skin images obtained through a dermatoscope. These images offer detailed views of skin lesions and are labeled by senior dermatologists of diverse origins. The dataset encompasses images divided into seven different groups, making it a valuable resource for training and evaluating machine learning algorithms for skin cancer diagnosis. Similarly, the ISIC dataset, freely available from the dermatology team of the Medical University of Vienna, serves as a benchmark for performance evaluation. Both datasets present challenges due to the large number of images and high visual similarity among different classes. Approximately half of the samples in the HAM10000 dataset have been verified using histopathology, while the status of the remaining samples is under review.

d) Data Processing:

In the data processing stage for skin image analysis, two crucial steps are undertaken: image resizing and image augmentation. Firstly, all images in the dataset are resized to a standard size of 100x100 pixels. This standardization facilitates input to machine learning models, particularly convolutional neural networks (CNNs) like DenseNet. Standardizing image sizes ensures uniformity in input data, aiding model training and generalization. By presenting images in a consistent format, the model can learn more effectively and make predictions without the complexity of handling varied image sizes during testing.

Secondly, image augmentation techniques are applied to further enrich the dataset. Augmentation involves applying transformations such as flipping, rotating, shearing, and zooming to generate multiple versions of each image. These modifications introduce variability, enhancing the diversity of the training data. By exposing the model to a broader range of scenarios, augmentation helps prevent overfitting and improves the model's ability to generalize to real-world variations. The augmented dataset with these transformed images enables the model to learn more robust features, leading to enhanced accuracy and reliability in its predictions. Overall, data processing through resizing and augmentation plays a vital role in preparing the dataset for training, ultimately contributing to the practicality and effectiveness of the machine learning model for skin cancer diagnosis.

e) Label Encoding:

In the label encoding step, the categorical target labels representing the 7 skin cancer classes are converted into numerical values. Each class is assigned a unique encoded value ranging from 0 to 6, as follows: Melanocytic nevi (0), Melanoma (1), Benign keratosis-like lesions (2), Basal cell carcinoma (3), Actinic keratoses (4), Vascular lesions (5), and Dermatofibroma (6). This transformation facilitates machine learning model training, as algorithms typically require numerical inputs. By converting categorical labels into a binary class matrix, the model can effectively classify skin cancer types based on the encoded numerical representations.

f) Training & Testing:

After balancing the dataset, we utilized the train-test split approach to partition the dataset into two sets: the training set and the test set. The training set, comprising 80% of the data, consisted of 21,252 samples, while the test set contained 20% of the data, totaling 5,313 samples. The training set was utilized to train the machine learning model, enabling it to learn patterns and features from the data. Subsequently, the test set was employed to evaluate the model's performance, assessing its ability to generalize to unseen data and make accurate predictions.

g) Algorithms:

CNN:

Convolutional Neural Networks (CNNs) are specialized neural networks designed to handle spatial structures, particularly suited for image data. Inspired by the visual system of mammals, CNNs feature fewer parameters than traditional neural networks, enabling the training of very deep models with over five layers. A typical CNN architecture includes an input layer, an output layer, and multiple hidden layers. These hidden layers often consist of convolutional, ReLU (activation function), pooling, fully connected, and normalization layers. CNNs excel in extracting and learning hierarchical features from images, making them highly effective for tasks such as image classification, object detection, and segmentation

h) CNN Model Architecture:

The CNN for image classification starts with a convolutional layer of 96 filters (11x11) with a stride of 4, processing 100x100x3 RGB images, with ReLU activation, batch normalization and max pooling. The second convolutional layer has 256 filters (5x5) with a stride of 1 and 'same' padding, ReLU activation, batch normalization and max pooling with 3x3 window and stride 2. The third layer has 384 filters (3x3) with a stride of 1 and 'same' padding, ReLU activation and batch normalization. The fourth layer has 384 filters but with 1x1 filter size, ReLU activation and batch normalization. The fifth layer has 256 filters (1x1), ReLU activation, batch normalization and max pooling. Then the output is flattened and fed into a dense layer of 4096 neurons with ReLU activation, followed by a dropout layer of 0.5. Another dense layer of 4096 neurons with ReLU activation and another dropout layer. The final dense layer has 7 neurons with softmax activation to give a probability distribution over the 7 classes. This CNN can handle complex image classification tasks by extracting features at multiple levels and techniques to improve training efficiency and robustness.

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	Layer Type	Input Shape	Parameters	Output Shape
Layer -1	Conv2D	(100, 100, 3)	filters=96 kernel_size=(11, 11) strides=(4, 4) activation='ReLU'	(23, 23, 96)
	Batch Normalization	(23, 23, 96)		(23, 23, 96)
	MaxPool2D	(23, 23, 96)	pool_size=(3, 3) strides=(2, 2)	(11, 11, 96)
Layer -2	Conv2D	(11, 11, 96)	filters=256 kernel_size=(5, 5) strides=(1, 1) activation='ReLU' padding='same'	(11, 11, 256)
	Batch Normalization	(11, 11, 256)		(11, 11, 256)
	MaxPool2D	(11, 11, 256)	pool_size=(3, 3) strides=(2, 2)	(5, 5, 256)
Layer - 3	Conv2D	(5, 5, 256)	filters=384 kernel_size=(3, 3) strides=(1, 1) activation='ReLU' padding='same'	(5, 5, 384)
	Batch Normalization	(5, 5, 384)		(5, 5, 384)
Layer - 4	Conv2D	(5, 5, 384)	filters=384 kernel_size=(1, 1) strides=(1, 1) activation='ReLU' padding='same'	(5, 5, 384)
	Batch Normalization	(5, 5, 384)		(5, 5, 384)
Layer - 5	Conv2D	(5, 5, 384)	filters=256 kernel_size=(1, 1) strides=(1, 1) activation='ReLU' padding='same'	(5, 5, 256)
	Batch Normalization	(5, 5, 256)		(5, 5, 256)
	MaxPool2D	(5, 5, 256)	pool_size=(3, 3) strides=(2, 2)	(2, 2, 256)
Others	Flatten	(2, 2, 256)		1024
	Dense	1024	units=4096 activation='ReLU'	4096
	Dropout	4096	rate=0.5	4096
	Dense	4096	units=4096 activation='ReLU'	4096
	Dropout	4096	rate=0.5	4096
	Dense	4096	units=7 activation='SoftmMax'	7

Fig 3 CNN Model Architecture.

j) Model Training:

The CNN is trained epoch by epoch, each epoch being a full pass through the entire training dataset, with a batch size of 32. This batch size allows for more frequent weight updates and faster convergence and generalization. The Adam optimizer is used because it's fast and has adaptive learning rate. Adam combines the advantages of AdaGrad and RMSProp. It calculates individual learning rates for each parameter based on the first and second moments of the gradients. It's good for tasks with sparse data and dynamic objectives.

```
FUNCTION Preprocess_Data(images,targets)
  resized_data = Resize(images, (100, 100))
  augmented_data = Image_Augmentation(resized_data) #rotate, flip, zoom
  encoded_targets = Encode_Targets(targets)
  RETURN resized_data, encoded_targets

images, targets = Load_Dataset()

preprocessed_data, encoded_targets = Preprocess_Data_Data(images,targets)

X_train, X_test, Y_train, Y_test = Split_Data(preprocessed_data, encoded_targets, 0.8)

model = Define_CNN_Model(input_shape=(100, 100, 3), conv2d_layers = 5,dense_layers = 3)

model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])

for epoch in range(num_epochs):
  model.fit(X_train, Y_train, batch_size=32, epochs=1, validation_data=(X_test, Y_test))
  early_stopping.on_epoch_end(epoch, logs=model.history.history)
  model_checkpoint.on_epoch_end(epoch, logs=model.history.history)

loss, accuracy = model.evaluate(X_test, Y_test)

Deploy_Model(model)
```

Fig 4 Pseudo Code of System

To improve performance and prevent overfitting, the training process uses Early Stopping and Model Checkpointing. Early Stopping monitors the validation loss at the end of each epoch and stops training if no improvement is seen for a certain number of epochs. Model Checkpointing saves the model's weights when the validation loss improves. Also, validation is done at the end of each epoch so we have an unbiased measure of the model's performance and not just memorizing the training data but can generalize well to new data.

i) Training Evaluation:

The metrics and plots show the performance of the model over 100 epochs. The training accuracy goes up steadily to 91% by the end which means the model is learning and fitting the training data well. So the model architecture and training process is good for skin cancer classification. But high training accuracy is not enough; the model should generalize well to unseen data. The validation accuracy is trending up but has big fluctuations especially in the initial epochs which means overfitting. Despite the fluctuations the validation accuracy stabilizes at 80% which means decent performance but need further fine tuning to generalize better.

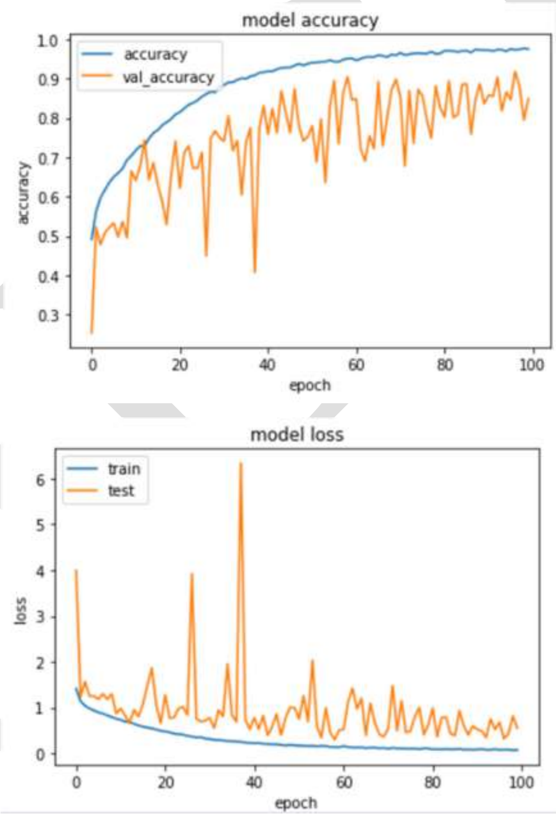

Fig 5 Model Loss and Accuracy Plot

The loss plots give more info about the training process. The training loss is going down which means the model is getting better at minimizing the errors on the training set. The validation loss has big fluctuations especially around epoch 40 which might be due to overfitting or variations in the validation subsets. Despite that the validation loss is going down at the end which means better generalization.

j) Frontend Integration:

After deploying the trained CNN model, built a frontend application using Python's Streamlit framework (Open Source web development framework). The uploaded images are processed and fed into the deployed model which is loaded from the. hdf5 file. The model does the work and gives a prediction and then displays it to the user through the web app.

4. EXPERIMENTAL RESULTS

a) Confusion Matrix:

The skin cancer model performs well for Vascular lesions and Dermatofibroma with 100% and high accuracy respectively. However, there is confusion among Melanocytic nevi, Melanoma and Benign keratosis-like lesions with many misclassifications between these classes. For example, Melanocytic nevi are often misclassified as Melanoma and Benign keratosis-like lesions and Melanoma is also misclassified into similar categories. Actinic keratoses are confused with Benign keratosis-like lesions and Basal cell carcinoma, we need to improve feature extraction and more training data to differentiate these similar skin lesion types.

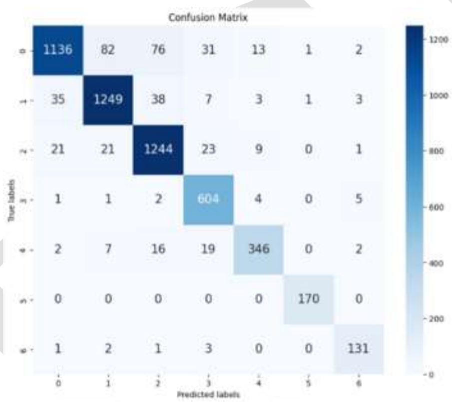

Fig 6 Confusion Matrix

b) Evaluation Metrics:

The skin cancer classification model performs well overall with 91.85% accuracy and good precision, recall and F1 score (92.43%, 93.37%, 92.80% respectively). These numbers show the model is good at diagnosing different types of skin cancer and balancing sensitivity and specificity which is important in medical diagnosis to avoid false positives and negatives.

Evaluation Metric	Values
Accuracy	91.85%
Precision	92.43%
Recall	93.37%
F1 Score	92.80%

Fig 6 Evaluation Metrics

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Class accuracies vary, the model is good at Melanoma (93%), Benign keratosis-like lesions (94%) and Basal cell carcinoma (98%) but not so good at Melanocytic nevi (85%) as they are similar to other lesions. Actinic keratoses is 88% accurate, good but needs more training data and better feature extraction.

c) Application Results:

Users interact with the skin cancer classification frontend by visiting the site, selecting "Upload Images" to attach their photos, and clicking "Predict" to trigger backend processing with pre-trained models. The analysis results are displayed on the webpage immediately after classification.

Fig 7 Home Page

Fig 8 Accepted Terms and Uploaded Image

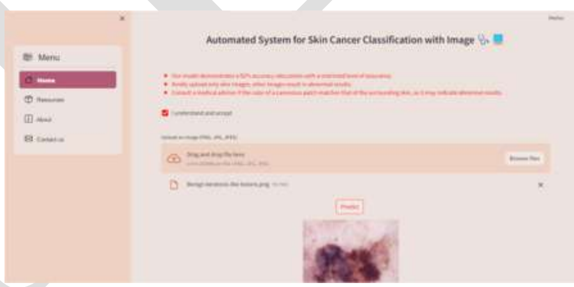

Fig 9 Prediction Results

Fig 10 Analysis of Uploaded Skin Cancer Image

5. CONCLUSION

In conclusion, the skin cancer classification model presented in this study demonstrates remarkable accuracy, with an overall performance of 91.85%. This level of accuracy, coupled with the practicality of the frontend application developed using Python Streamlit, signifies the potential of our model for deployment in clinical environments. The success of our approach can be attributed to meticulous preprocessing steps, effective data augmentation techniques, and a robust convolutional neural network architecture.

Despite the promising results achieved, there remains sample room for future improvement and enhancement. Incorporating advanced techniques like transfer learning, as demonstrated by studies achieving up to 98.16% accuracy, can further boost our model's performance by leveraging pre-trained models on large datasets. Additionally, employing ensemble learning methods can enhance accuracy by combining multiple models to mitigate individual weaknesses and provide more robust predictions.

6. FUTURE SCOPE

In the future, further advancements can be made in skin cancer classification by exploring techniques like transfer learning and ensemble learning to enhance model accuracy. Expanding the dataset to include a wider variety of skin types and demographics will improve generalizability. Integration with electronic health records and batch processing capabilities can streamline clinical workflow. Additionally, real-time feedback mechanisms can facilitate continuous model refinement. These enhancements aim to bolster the model's performance, accessibility, and utility in clinical practice, ultimately contributing to more effective and efficient skin cancer diagnosis and management.

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