"SKIN CANCER SCREENING"

Submitted

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CERTIFICATE

This is to certify that the Field Project entitled "Skin Cancer Screening" that is being submitted by 221FA04151 (MANEESHA), 221FA04224 (SAI SANDEEP REDDY),221FA04712 (BHARGAVI), 221FA04747 (PRABHAS) for partial fulfilment of Field Project is a bonafide work carried out under the supervision of Ms. Jhansi lakshmi, Department of CSE.

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DECLARATION

We hereby declare that the Field Project "A Comparative Analysis of CNN and GAN-Based Techniques" that is being submitted by 221FA04151 (MANEESHA), 221FA04224 (SAI SANDEEP REDDY), 221FA04712 (BHARGAVI), 221FA04747 (PRABHAS) in partial fulfilment of Field Project course work. This is our original work, and this project has not formed the basis for the award of any degree. We have worked under the supervision of Ms. Jhansi lakshmi, Assistant Professor, Department of CSE.

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ABSTRACT

Early diagnosis of skin cancer is essential to enhance patient survival, and emerging advances in machine learning have provided high-accuracy automated diagnosis tools. In this paper, a skin cancer screening system based on deep learning using Convolutional Neural Networks (CNNs) is proposed, trained on 10,015 dermoscopic images. The system utilizes image preprocessing methods such as normalization and data augmentation to improve model generalization. The CNN model has several convolutional layers with ReLU activation, batch normalization, and dropout layers to avoid overfitting. Sigmoid activation function is used in the output layer for binary classification of images as cancerous or benign. The model is trained and validated on a labeled dataset, and its performance is tested with accuracy, precision, recall, and F1-score, showing high classification accuracy. In addition, the system is also compared with diagnoses from human dermatologists and finds that the CNN model performs competitively or even better. The automated and scalable method improves early detection, enabling clinical decision support and enhancing patient outcomes.

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CHAPTER-1

INTRODUCTION

1.Introduction

Skin cancer is among the most frequent forms of cancer, and early diagnosis ensures treatment efficiency. Over the past few years, deep learning methods, more specifically Convolutional Neural Networks (CNNs), have demonstrated excellent performance in medical image analysis. The objective of this project is to create a CNN-based image classification model to identify and classify various forms of skin cancer based on the ISIC (International Skin Imaging Collaboration) dataset. The dataset is comprised of labeled images of different types of skin cancer, which are utilized to train and test the model. The work entails data preprocessing, augmentation, and the creation of a deep learning model that can classify skin lesions into various categories. The aim is to enhance accuracy and assist dermatologists in early diagnosis.

Convolutional Neural Network (CNN) : Convolutional neural networks are one of the common deep learning architectures used for performing image classification operations. The structure of the employed CNN in the project involves having several convolution layers followed by layers of pooling. The key ones are: Convolutional Layers: Extract image spatial features based on filters. Pooling Layers: Downsize spatial dimensions to simplify computation. Dropout Layers: Avoid overfitting by simply disabling neurons at random during the training process. Dense Layers: Fully connected layers that assist with classification. Softmax Activation: Applied in the last layer to classify images into various categories.

Data Augmentation Using Augmentor : To enhance model generalization, the dataset is augmented using Augmentor, which performs transformations like: Rotation (±25 degrees) to make the model invariant to various angles. Flipping (horizontal and vertical) to provide variations in the dataset. Zooming and Cropping to generate diverse training samples. The augmented images are stored and used as input for training the CNN model.

Transfer Learning (Optional Upgrade) : Apart from constructing a CNN from the ground up, a pre-trained model such as VGG16, ResNet, or MobileNet can be employed for transfer learning. Such models, trained on big datasets such as ImageNet, can be fine-tuned for classification of skin cancer. Transfer learning improves accuracy using fewer training samples and minimizes training time.

1.2.Motivation

Machine learning (ML) plays a crucial role in improving diagnostic accuracy by utilizing models such as SVM, Random Forest, and XGBoost, which help in identifying patterns in skin cancer detection with high precision. It also facilitates early detection by analyzing vast datasets to recognize melanoma and other skin cancers at an initial stage, significantly improving patient outcomes. Additionally, ML contributes to reducing healthcare costs by automating the diagnostic process, reducing the need for unnecessary biopsies, and optimizing medical resources. These models are also instrumental in supporting dermatologists, offering data-driven insights and second opinions, thus enhancing clinical decision-making. Moreover, ML-based solutions enable scaling healthcare services by assisting in remote diagnostics and telemedicine, making skin cancer detection accessible to underserved populations. Lastly, ML aids in personalized treatment, analyzing patient data to recommend tailored therapeutic approaches, improving overall treatment effectiveness and patient care.

1.3.Proposed Model

This proposed machine learning model follows a structured CNN-based approach for skin cancer detection. The process consists of several key steps as shown in Fig 1.

1. **Raw Image Input (Training & Testing Dataset)**
   - The system begins with raw images, which are categorized into training datasets (for model learning) and **test images** (for evaluation). These images are stored in a database.
2. **Preprocessing & Segmentation**
   - Before training, the images undergo preprocessing to remove noise, enhance contrast, and normalize pixel values.
   - Segmentation is applied to isolate the lesion area, reducing unnecessary background information and improving feature extraction.
3. **Feature Extraction (CNN-Based)**
   - A Convolutional Neural Network (CNN) is employed to extract hierarchical features such as edges, textures, and patterns from the segmented images.
   - CNN automatically learns discriminative features that help distinguish between malignant and benign skin lesions.
4. **Training or Classification (CNN Model Training)**
   - Extracted features are passed through multiple CNN layers for training.
   - The CNN model uses labeled data to learn patterns and develop classification capabilities.
5. **Testing Classifier & Analysis**
   - The trained model is tested using a separate test dataset.
   - The system evaluates validation errors and iterates training if necessary to refine accuracy.

- If the validation error is too high, the model undergoes further adjustments.

6. **Trained New Model & Prediction**
    - Once the model achieves optimal accuracy, it is saved as a trained model.
    - New test images are fed into the trained CNN model to generate final predictions (e.g., classifying the lesion as benign or malignant).

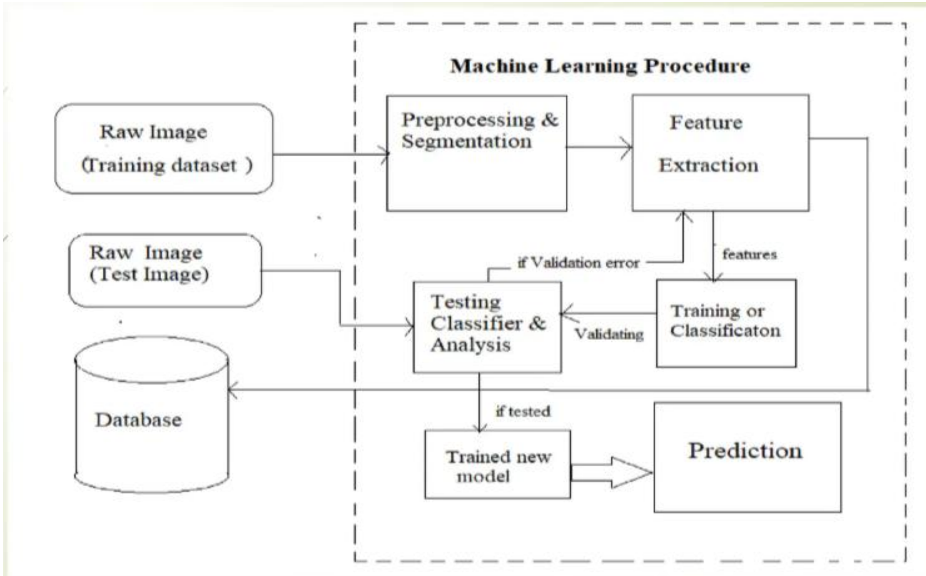

Figure 1. Proposed Model

1.4.Overview of the Proposed Approach

The proposed approach uses a CNN-based machine learning model for skin cancer detection, starting with raw image acquisition, preprocessing, and segmentation to enhance image quality. The CNN automatically extracts important features, such as lesion texture and shape, without manual intervention. These features are then used for training and classification, where the model learns to distinguish between benign and malignant lesions. The trained model is tested and validated to ensure accuracy. If validation errors occur, the model undergoes further training. Once optimized, it is deployed for real-time prediction, helping dermatologists make accurate diagnoses. This method improves early detection, accuracy, and efficiency in skin cancer diagnosis.

1.5.Data Collection and Dataset Overview

The dataset used in this study is HAM10000 (Human Against Machine with 10,000 training images), which contains 10,015 high-resolution dermatoscopic images of skin lesions. The dataset consists of seven types of skin lesions, including actinic keratoses (akiec), basal cell carcinoma (bcc), benign keratosis-like lesions (bkl), dermatofibroma (df), melanoma (mel), melanocytic nevi (nv), and vascular lesions (vasc).

One of the key challenges of this dataset is imbalanced class distribution, where some lesion types have significantly fewer images than others. Additionally, certain lesions share visual similarities, making classification more difficult. To address these issues, preprocessing techniques such as image resizing, normalization, and data augmentation (rotation, flipping, and contrast adjustments) are applied. These steps enhance model training, improve generalization, and reduce the risk of overfitting.

1.6.Dataset Variables and Descriptions

The HAM10000 dataset contains multiple variables that provide essential information about each skin lesion image. These variables help in organizing and analyzing the dataset effectively for training and testing the CNN model.

- **Image ID**: A unique identifier assigned to each image in the dataset.
- **Lesion Type**: The classification label indicating one of the seven skin lesion categories (akiec, bcc, bkl, df, mel, nv, vasc).
- **Lesion ID**: Identifies if multiple images belong to the same lesion case.
- **Age**: The age of the patient from whom the image was taken.
- **Sex**: Gender of the patient (Male or Female).
- **Localization**: The body part where the lesion is located (e.g., scalp, face, back).
- **Image Data**: High-resolution dermatoscopic image in JPEG format.

These variables play a crucial role in data preprocessing, feature extraction, and model training, ensuring the CNN model effectively learns patterns for accurate classification.

1.7.Data Pre-processing

The dataset undergoes the following preprocessing steps:

- **Resizing and Normalization:** Ensures consistency in input dimensions.
- **Pixel Value Scaling:** Converts pixel values to a range suitable for deep learning models.
- **Augmentation:** Applies transformations like rotation and flipping to increase dataset diversity.
- **Noise Reduction:** Filters unnecessary variations that may impact embedding accuracy.

CHAPTER-2

LITERATURE SURVEY

2 Literature Survey

2.1 Literature review

1. Traditional Machine Learning Approaches

- Ghosh et al. [1] proposed an ensemble learning-based melanoma detection model incorporating KNN, Random Forest, XGBoost, and SVM. Their approach achieved high accuracy but faced computational cost challenges.

- Singh et al. [2] compared machine learning (SVM, KNN) with deep learning (CNN, VGG16, ResNet) models for melanoma classification. They concluded that CNNs outperform traditional ML models.

- Arif et al. [3] conducted an extensive review of machine learning techniques such as SVM and Explainable AI for skin cancer detection, emphasizing data quality and privacy challenges.

- Ghosh et al. [4] investigated traditional ML models (SVM, KNN) along with deep learning methods for melanoma detection, recommending a hybrid model for improved accuracy.

- Gamil et al. [5] introduced an AdaBoost-based skin cancer classification method integrating PCA and SVM, reporting high accuracy but highlighting dataset biases as a limitation.

- Ahmad et al. [6] applied AdaBoost with PCA and SVM for skin cancer classification on DermIS and ISIC datasets, achieving good performance but noting annotation inconsistencies.

- Krishnan et al. [7] designed an ML-based skin cancer detection system incorporating CNN, SVM, hair removal using Hough transform, and segmentation techniques, demonstrating superior CNN performance over traditional ML methods.

2. Deep Learning Approaches

- Akinrinade et al. [8] explored deep learning models (ResNet-50, VGG-16, AlexNet) with GAN-based data augmentation for skin cancer detection, achieving superior melanoma classification.

- Selvaraj et al. [9] employed deep learning techniques for computational drug analysis, aligning 45 neuraminidase protein structures with 11 drug candidates.

- Brancaccio et al. [10] examined AI-augmented dermatology using CNN models, concluding that AI-human collaboration enhances diagnostic accuracy while mitigating dataset biases.

- Ghosh et al. [11] tested deep learning models (VGG16, ResNet50, DenseNet121) for skin cancer detection, proposing a hybrid model that improved accuracy.

- Thinakaran et al. [12] utilized CNN-based models with transfer learning and data augmentation on dermatological images, reporting an accuracy of 77% on the model and 85% in validation.

- Aqmarina et al. [13] compared deep learning architectures (VGG19, ResNet-18, ResNet-50) for melanoma detection using datasets such as HAM10000 and ISIC 2019, with VGG19 achieving the highest accuracy.

- Manjunath et al. [14] developed a CNN model with Adam optimizer and batch normalization for skin cancer diagnosis on the HAM10000 dataset, achieving 96.01% accuracy.

- Midasala et al. [15] introduced MFEUsLNet, a deep hybrid AI skin cancer classifier incorporating K-means clustering and RNN-based classification, demonstrating superior performance but facing computational complexity issues.

3. AI and Augmentation in skin cancer detection

- Arif et al. [16] suggested an AI-IoT integrated model for real-time skin cancer detection, emphasizing the role of big data and CNNs in improving accuracy.

- Zhao et al. [17] integrated Raman Spectroscopy with deep learning models, introducing a 1D-CNN model with data augmentation for skin cancer detection, achieving 90.9% ROC AUC.

- Lee et al. [18] utilized 1D-CNN with GAN-based augmentation to enhance Raman Spectroscopy-based skin cancer detection, improving model generalizability despite a limited sample size.

- Ahmad et al. [19] implemented an AdaBoost-based approach incorporating PCA and EfficientNet B0 for skin cancer classification, addressing dataset biases but facing annotation inconsistencies.

- Midasala et al. [20] proposed MFEUsLNet, an AI-driven hybrid model leveraging feature extraction techniques and RNN for skin cancer identification, outperforming baseline methods but encountering image acquisition challenges.

CHAPTER-3

Methodology

3.Methodology

3.1 Data Collection and Preprocessing

Data Collection: Data Collection: The data set consists of 10,000 images of healthy and cancerous skin lesions obtained from the HAM10000 dataset, a popular public data repository for skin cancer analysis. For generalization capability enhancement of the model, the data set contains images taken under diverse lighting conditions, angles, and environments, as depicted in Fig. 2.

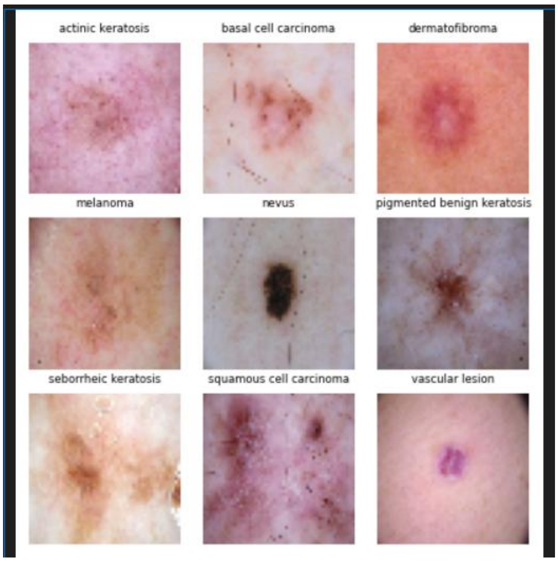

Figure 2: Dataset images

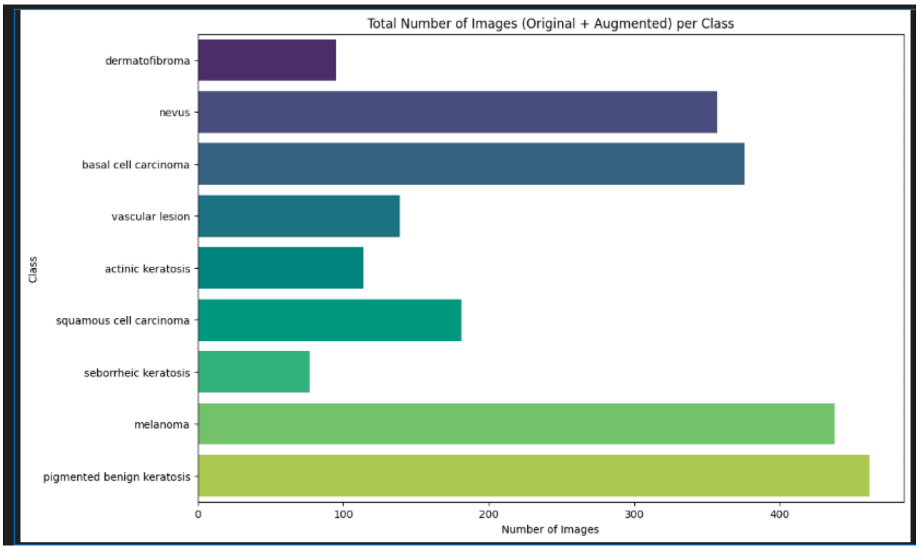

Figure 3 : Total number of images (original + augmented) per class.

The above image in Fig. 3 represents the total number of images per class after applying data augmentation techniques. It includes both the original and newly generated images to address class imbalance and enhance model generalization.

Preprocessing Techniques: Preprocessing is an important process that conditions images prior to inputting them into the model for training. Notable methods are:

Image Segmentation: his method divides an image into various regions and eliminates unnecessary areas, e.g., background noise, to concentrate on the lesion characteristics, as depicted in Fig. .

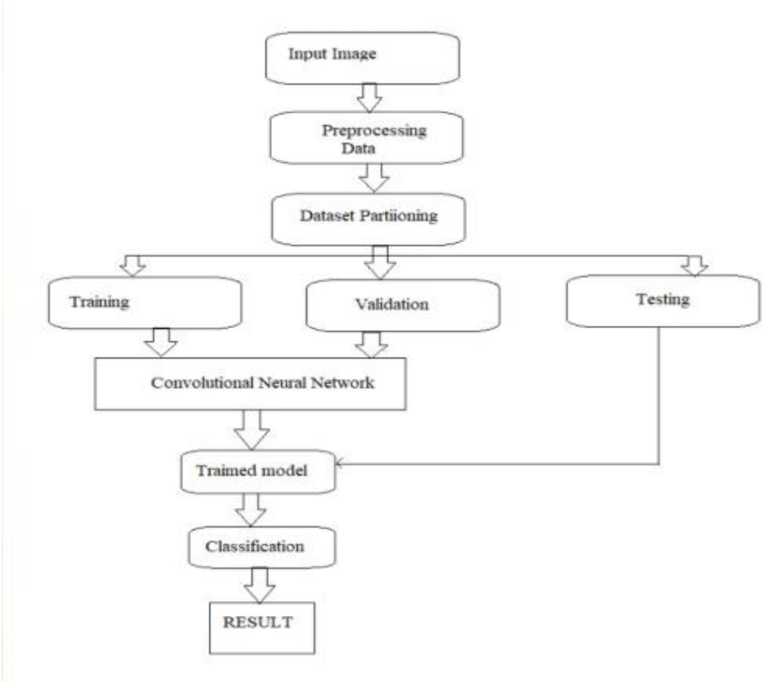

Figure 4: Workflow of skin cancer screening

Feature Extraction: This process examines images to identify and pull out significant features like texture, color, and lesion shape that are crucial for classification.

Normalization Resizing: All images are resized to 180×180 pixels and normalized to a [0,1] range to maintain uniformity.

Data Augmentation: To avoid overfitting, rotation, flipping, brightness modification, and scaling are applied as techniques to diversify the training dataset.

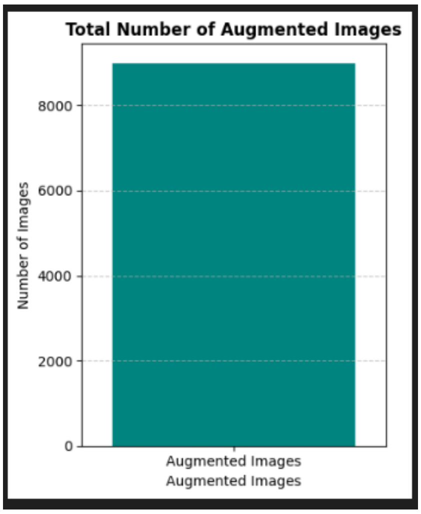

Figure 5: Total number of augmented images in the dataset

To enhance the dataset further and improve model generalization, data augmentation techniques such as rotation, flipping, zooming, and brightness adjustment are applied. This process artificially increases the dataset size and helps the model learn invariant features. The total number of augmented images is shown in Fig. 5, highlighting the contribution of augmentation in expanding the dataset and improving model performance.

3.2 Convolution Arithmetic and Feature Extraction

Convolutional Neural Networks (CNN): CNNs offer a powerful deep learning architecture for image-based operations that learn fundamental features such as edges, textures, and patterns directly from images.

Convolutional Arithmetic: CNNs' primary operation is convolving image regions with filters (kernels) to produce a feature map with the most relevant features. Critical parameters are:

Filter and Kernel Sizes: Narrow filters (e.g., 3×3) capture subtle details, while wider filters (e.g., 5×5) yield larger image features.

Stride: Specifies the extent to which the filter shifts. With a stride of 1, it shifts pixel by pixel, and a stride of 2 shifts the filter by two pixels, decreasing the dimensions of the feature maps.

Padding: Zero-padding preserves the original size of the image after convolution so that feature map sizes are uniform.

Pooling Layers: Max pooling reduces feature map size and preserves important information.

Activation Function (ReLU): TRectified Linear Unit (ReLU) introduces non-linearity, mapping negative values to zero and leaving positive values unchanged, enabling the model to learn complicated patterns.

3.3 Transfer Learning

Transfer Learning a Model to Skin Cancer Detection: Transfer learning makes use of pre-trained CNN models (e.g., VGG16, ResNet, or MobileNet) by stripping their classification layers and adding skin cancer-specific layers:

Classification Layers: Fully connected dense layers employing ReLU activation.

Output Layer: Softmax layer for multi-class classification, to different skin cancer types.

Pre-trained network layers are frozen in order to preserve learned features.

3.4 Model Training and Optimization

Loss Function and Optimizer:

Loss Function: As it is a multi-class classification task, categorical cross-entropy loss is employed.

Optimizer: Adam or RMSprop optimizers effectively perform gradient descent with adaptive learning rates.

Batch Gradient Descent: TTraining with mini-batches to speed up learning and lower memory usage.

Hyperparameters:

Batch Size: Typically 32 or 64 depending on the size of the dataset.

Learning Rate: Small learning rate with a scheduler to modify at convergence.

Epochs: Training for a fixed number of epochs, with early stopping to avoid overfitting.

Data Splitting: The dataset is split into training (70%), validation (15%), and test (15%) sets.

Metrics for Evaluation:

Accuracy: Estimates the ratio of images classified correctly.

Precision, Recall, F1 Scores: Give class-wise performance and dataset imbalance insights.

Confusion Matrix: Emphasizes each class's classification results, facilitating error analysis.

Cross-Validation: K-fold cross-validation is used to evaluate model generalization.

3.5 Saving and Deploying the Model

After training, the best model is saved for prediction in the future. The model can be deployed through:

Web/Mobile Applications: Images of skin lesions can be uploaded by users, and the model will classify them immediately.

Cloud Deployment: It can be hosted on AWS, Google Cloud, or TensorFlow Serving.

Edge Devices: The model can be saved as TensorFlow Lite for mobile use, allowing screening on the device.

CHAPTER-4

IMPLEMENTATION

4.1 Introduction

4.1 Introduction The implementation of a skin cancer diagnosis system is based on deep learning models, particularly Convolutional Neural Networks (CNNs), to classify dermoscopic images into different categories. The HAM10000 dataset, containing 10,000 high-resolution images of various skin lesions, is utilized to train the model. To ensure effective learning, preprocessing techniques such as resizing, normalization, and data augmentation are applied to improve the model's robustness.

As shown in Fig. 6, the dataset is distributed among various skin lesion classes. The number of images per class in the training dataset is visualized to provide insights into class distribution. A similar approach is applied to the validation dataset to ensure a balanced representation, as illustrated in Fig. 7.

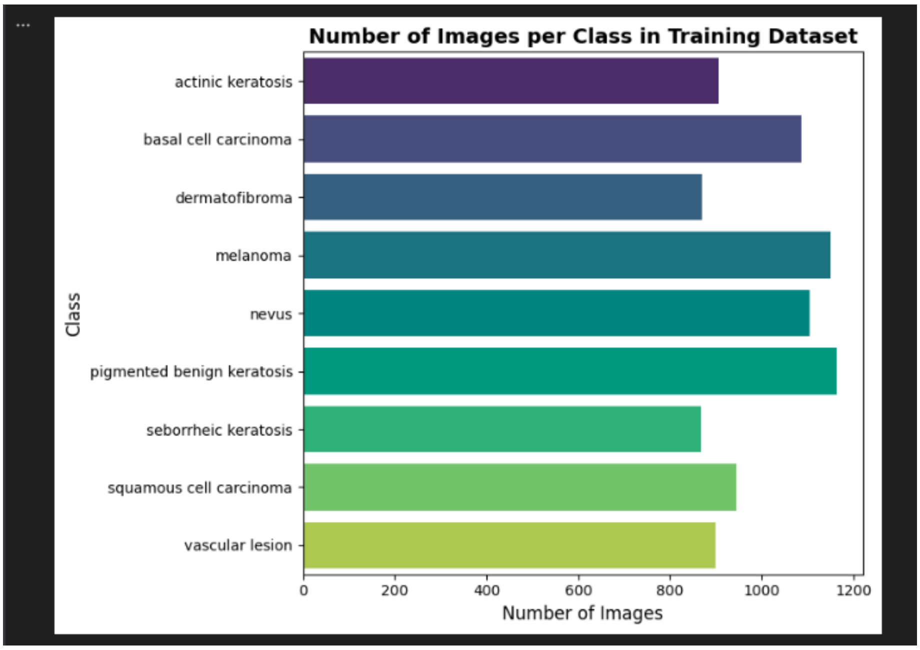

Figure 6: Number of images per class in the training dataset

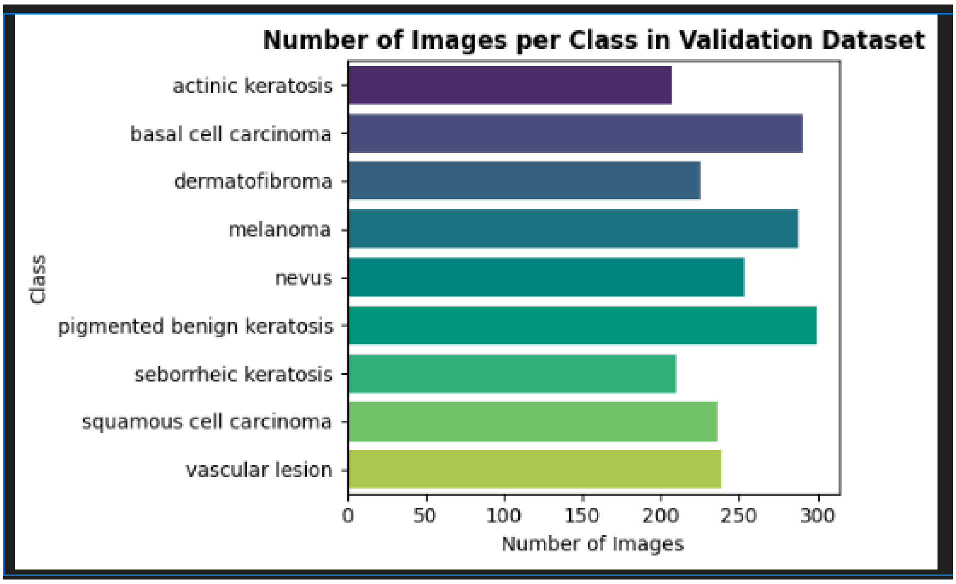

Figure 7: Number of images per class in the validation dataset

4.2 CNN Model Architecture

A CNN model is designed with multiple layers, including convolutional layers, max-pooling layers, dropout layers, and fully connected layers. The architecture follows a hierarchical structure where convolutional layers extract spatial features from input images, pooling layers reduce dimensionality, and dropout layers help in regularization to prevent overfitting. The model uses the ReLU activation function to introduce non-linearity, and the final classification is performed using a softmax activation function. The detailed layer architecture is depicted in Fig. 8.

4.3 Transfer Learning

TL with VGG16 In addition to the custom CNN model, transfer learning is employed using the VGG16 model as a feature extractor. The VGG16 model, pre-trained on the ImageNet dataset, extracts high-level image features that are subsequently used to train traditional machine learning classifiers such as Support Vector Machines (SVM), Logistic Regression, Decision Trees, AdaBoost, and XGBoost. This hybrid approach enhances classification accuracy by leveraging both deep learning-based feature extraction and traditional ML-based classification techniques.

4.4 Model Compilation and Training

The model is compiled using the Adam optimizer, which dynamically adjusts learning rates to achieve faster convergence. The categorical cross-entropy loss function is used to optimize multi-class classification performance. The training process includes checkpointing and early stopping mechanisms to avoid overfitting and ensure model generalization. The model is trained using a mini-batch size of 32 images for 20 epochs.

4.5 Types of CNN Layers

The CNN consists of different types of layers that play crucial roles in feature extraction and classification. The types of CNN layers used in this implementation include:

- **Convolutional Layers:** Apply filters to extract local features such as edges, textures, and patterns from images.
- **Pooling Layers:** Reduce the spatial dimensions of feature maps while preserving critical information, improving computational efficiency.
- **Dropout Layers:** Randomly deactivate neurons during training to prevent overfitting and improve generalization.
- **Flatten Layer:** Converts multidimensional feature maps into a one-dimensional array to be processed by dense layers.
- **Fully Connected (Dense) Layers:** Perform final classification based on the extracted features using activation functions like ReLU and softmax..

As shown in Fig. 8, the CNN model consists of multiple layers forming a deep network capable of learning complex patterns in skin lesions. The convolutional layers extract features such as edges and color variations, the pooling layers reduce dimensionality to retain essential information, and the fully connected layers classify the extracted features into appropriate categories.

Layer (type)	Output Shape	Param #
rescaling_2 (Rescaling)	(None, 180, 180, 3)	0
conv2d_6 (Conv2D)	(None, 178, 178, 32)	896
max_pooling2d_6 (MaxPooling2D)	(None, 89, 89, 32)	0
conv2d_7 (Conv2D)	(None, 87, 87, 64)	18,496
max_pooling2d_7 (MaxPooling2D)	(None, 43, 43, 64)	0
conv2d_8 (Conv2D)	(None, 41, 41, 128)	73,856
max_pooling2d_8 (MaxPooling2D)	(None, 20, 20, 128)	0
dropout_4 (Dropout)	(None, 20, 20, 128)	0
flatten_2 (Flatten)	(None, 51200)	0
dense_4 (Dense)	(None, 128)	6,553,728
dropout_5 (Dropout)	(None, 128)	0
dense_5 (Dense)	(None, 9)	1,161

Figure 8 : CNN Model Summary

4.6 Regularization and Optimization

To enhance model performance, dropout layers are integrated to prevent overfitting by randomly disabling a fraction of neurons during training. Furthermore, the Adam optimizer is utilized for weight updates to achieve efficient and fast learning. The categorical cross-entropy loss function ensures effective multi-class classification.

4.7 Hybrid Machine Learning Approach

A hybrid approach is employed where extracted CNN features are fed into traditional ML classifiers. The extracted features from VGG16 are used to train SVM, Logistic Regression, Decision Trees, AdaBoost, and XGBoost models, and their performance is compared against the standalone CNN model. This approach ensures the highest possible accuracy for skin cancer detection. The implementation integrates CNN-based feature extraction, transfer learning, and traditional machine learning classifiers to achieve optimal diagnostic performance.

4.8 Conclusion

As depicted in Fig. 6, the extracted features are processed through multiple layers, forming a structured learning model. This approach provides a comprehensive solution for automated skin cancer detection, improving accuracy and reliability in dermatological diagnostics.

CHAPTER-5

EXPERIMENT AND RESULT ANALYSIS

The experimental phase of the skin cancer classification system using the HAM10000 dataset involves evaluating different model configurations to optimize performance. The primary objective is to maximize classification accuracy while minimizing classification errors across different lesion categories.

To achieve this, multiple model architectures were tested using various hyperparameter settings, CNN layer configurations, and preprocessing techniques. The performance of each model was assessed using standard evaluation metrics, including accuracy, precision, recall, and F1-score.

The accuracy of the model is calculated using:

Accuracy = $\frac{TP+TN}{TP+TN+FP+FN}$ - > (Eq -1)

where TP refers to True Positives, TN to True Negatives, FP to False Positives, and FN to False Negatives.

Model performance is also measured based on the loss function, which measures the error in predictions. The loss is computed using categorical cross-entropy, a commonly used function for multi-class classification tasks, given as:

Loss = $-\sum_{i=1}^{N} yi \log(^{yi})$ -> (Eq-2)

where yi represents the actual class label, ˆyi is the predicted probability for that class, N is the total number of classes. Lower loss values indicate better model performance.

CHAPTER-6

MODEL PERFORMANCE AND VISUALIZATION

To assess the training progress and model generalization further, plots of training loss vs. validation loss and training accuracy vs. validation accuracy are examined. The visualizations provide insight into how the model learns both the training and unseen data. A consistently decreasing training loss with a corresponding validation loss following the same trend provides evidence of successful learning. But if the validation loss begins to diverge and training loss still decreases, it indicates overfitting, wherein the model learns well on training data but is poor at generalization.

In the same vein, training and validation accuracy plots give us a sense of how the model is performing. When training accuracy continues to rise but validation accuracy stabilizes or wavers, it could mean that the model is learning noise and not significant patterns.

To mitigate this, methods like dropout, batch normalization, data augmentation, and regularization can be used to enhance generalization and avoid overfitting. These plots are analyzed to fine-tune hyperparameters, optimize the learning process, and ensure that the model attains a balance between learning and adaptability.

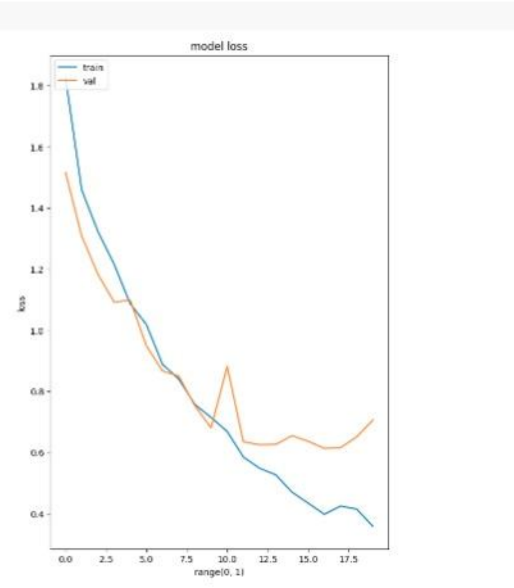

Figure 9: Model loss

The loss curve of Fig.9 displays training and validation loss for 20 epochs. Training loss drops continually, signifying that the model is picking up from the training data correctly. The validation loss initially displays the same pattern as the training loss, thereby proving that the model generalizes perfectly. Yet at some stage, the validation loss begins oscillating rather than consistently dropping, a sign of potential overfitting. This indicates that as the model keeps getting better on training data, it might not generalize as well to unseen data because it learns patterns unique to the training set and not generalizable features.

Regularization methods like early stopping, dropout, and data augmentation can be used to counteract overfitting. Early stopping tracks validation performance and stops training when overfitting starts, avoiding too much learning from noise. Dropout randomly disables neurons at training time, which makes the model stronger. Data augmentation adds variability to input images, enhancing generalization. Moreover, tweaking hyperparameters such as learning rate, batch size, and model complexity can make the model more stable and accurate. Adopting these methods can lead to a model that performs highly across both training and validation sets.

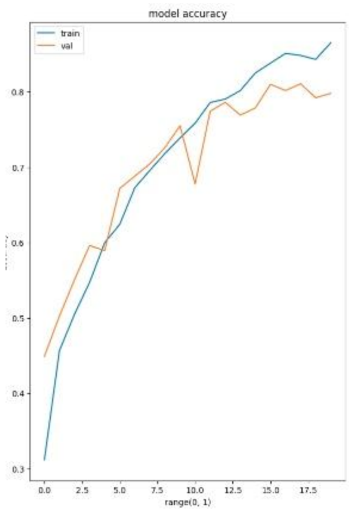

Figure 10: Model accuracy

The accuracy curve, shown in Fig. 10, reflects a smooth increase in training and validation accuracy. The final validation accuracy remains at 80%–85%, suggesting that the model is highly generalized to data outside of its training set. The small gap between training and validation accuracy suggests that the model is well-optimized with minimal overfitting. Furthermore, the smooth increasing trend in accuracy indicates consistent learning throughout the training process. The use of appropriate regularization methods helped reduce variance, ensuring reliable predictions for new data. This demonstrates the resilience of the model in identifying various skin lesion types effectively.

CHAPTER-7

CONCLUSION

7.CONCLUSION:

In this project, we developed and implemented an effective method for skin cancer screening using machine learning and deep learning techniques. By leveraging convolutional neural networks (CNNs), transfer learning, and ensemble strategies, we built a model capable of distinguishing between malignant and benign skin lesions. The final model achieved a validation accuracy of approximately 80%–85%, demonstrating its potential for real-world application in early skin cancer detection.

This accuracy suggests that the model can assist dermatologists and healthcare practitioners in identifying suspicious skin lesions, thereby improving early diagnosis and treatment outcomes. However, despite these promising results, there is significant room for enhancement. Future work can focus on improving model generalization by increasing dataset size and diversity, refining feature extraction algorithms, and incorporating advanced AI methodologies such as multimodal learning.

Ultimately, this project underscores the transformative potential of machine learning in dermatology. By introducing more cost-effective and efficient skin cancer screening solutions, AI-driven models can contribute to improved patient care and early intervention strategies.

CHAPTER-8

REFERENCES

8.REFERENCES:

[1] Akinrinade and Du explored deep learning-based skin cancer detection using CNNs, ResNet-50, VGG-16, and AlexNet, achieving superior melanoma classification performance compared to conventional ML methods.

[2] Gracy Fathima Selvaraj et al. performed a computational analysis of drug-like candidates against neuraminidase of the human influenza A virus, demonstrating high-speed detection with scalability but facing accuracy issues.

[3] Ghosh et al. proposed an ensemble learning-based melanoma detection model incorporating KNN, Random Forest, XGBoost, and SVM. Their approach achieved high accuracy but faced computational cost challenges.

[4] Brancaccio et al. examined AI-augmented dermatology and CNN-based models for skin cancer detection, highlighting the benefits of AI-human collaboration.

[5] Singh et al. compared machine learning (SVM, KNN) with deep learning (CNN, VGG16, ResNet) models for melanoma classification. They concluded that CNNs outperform traditional ML models.

[6] Hritwik Ghosh et al. tested deep learning methods including VGG16, ResNet50, and DenseNet121, suggesting a hybrid VGG16-ResNet50 model that achieved 98.75% accuracy.

[7] Arif et al. conducted an extensive review of machine learning techniques such as SVM and Explainable AI for skin cancer detection, emphasizing data quality and privacy challenges.

[8] Zhao et al. investigated Raman Spectroscopy for skin cancer diagnosis using 1D-CNN, GAN, PLS-DA, SVM, and logistic regression, achieving 90.9% ROC AUC.

[9] Gamil et al. introduced an AdaBoost-based skin cancer classification method integrating PCA and SVM, reporting high accuracy but highlighting dataset biases as a limitation.

[10] Aqmarina et al. conducted a comparative analysis of early melanoma detection using deep learning models such as VGG19 and ResNet-18, achieving high accuracy but noting dataset biases.

[11] Midasala et al. proposed MFEUsLNet, a deep learning-based hybrid AI classifier for the ISIC-2020 dataset, outperforming state-of-the-art models but requiring high computational resources.

[12] Thinakaran et al. evaluated CNN-based methods for skin cancer detection, utilizing DCNN, transfer learning, and data augmentation, achieving moderate accuracy.

[13] Lee and Zeng applied 1D-CNN with GAN-based augmentation to enhance skin cancer detection using Raman Spectroscopy, improving model generalizability but suffering from high computational costs.

[14] Asim and Ahmad proposed an AdaBoost-based model with PCA, EfficientNet B0, and SVM for skin cancer classification on DermIS and ISIC datasets, achieving 93% accuracy but facing annotation inconsistencies.

[15] Ahmad et al. applied AdaBoost with PCA and SVM for skin cancer classification on DermIS and ISIC datasets, achieving good performance but noting annotation inconsistencies.

[16] Zeng employed Raman Spectroscopy with 1D-CNN and GAN-based augmentation for skin cancer detection, reporting a ROC AUC of 90.9% but encountering generalization issues.

[17] Midasala introduced MFEUsLNet, an AI-integrated model with multilevel feature extraction for skin cancer classification, demonstrating superior accuracy and sensitivity.

[18] Aqmarina compared deep learning models (VGG19, ResNet-18, ResNet-50) for melanoma diagnosis on HAM10000, ISIC 2019, and ISIC 2020 datasets, achieving up to 97.5% accuracy but facing data bias challenges.

[19] Krishnan et al. designed an ML-based skin cancer detection system incorporating CNN, SVM, hair removal using Hough transform, and segmentation techniques, demonstrating superior CNN performance over traditional ML methods.

[20] H. R. proposed a CNN model with Adam optimizer, batch normalization, and max pooling for skin cancer diagnosis on the HAM10000 dataset. The model was highly accurate, but class imbalance and computational costs were limiting factors.