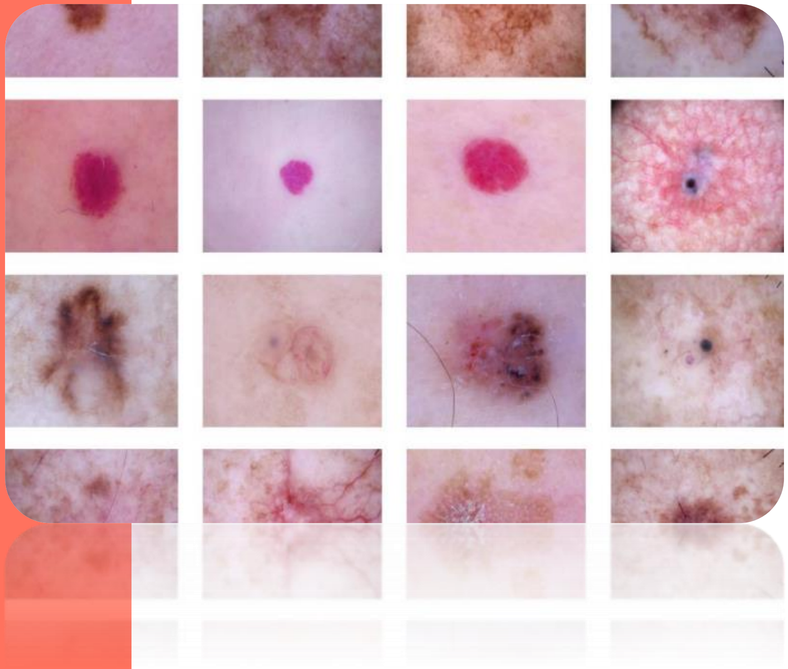
A Deep Learning Approach to Detecting Skin Lesion



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Dissertation Presentation

Presented By-
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Introduction

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- Skin cancer is a serious health problem for people all over the world, and over the past several decades, its prevalence has been rising quickly.
- Skin lesion detection is an essential task in dermatology as it assist medical practitioners in early detection of skin cancer.
- Traditional skin lesion detection methods take a lot of time, depend heavily on the knowledge of the doctor, and are often not available in rural areas.
- Deep learning, particularly Convolutional Neural Networks (CNNs), offers potential for skin lesion diagnosis.
- This research intends to overcome the limitations of the traditional methodology by providing a faster and broadly accessible method for finding and diagnosing skin lesions using deep learning approach.

Aim and Objectives

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Aim - The aim of the project is to develop an accurate web-based application for diagnosing various forms of skin lesions using deep learning models.

Objectives

- Conduct an extensive literature review to identify and analyse state-of-the-art deep learning approaches for skin lesion detection.
- Develop and optimise a robust deep learning model for accurate categorization of skin lesions using a CNN architecture, leveraging transfer learning and data augmentation approaches to improve performance.
- Provide a comprehensive evaluation and discussion of the customised CNN and transfer learning models.

Literature Review

Author	Approach	Key Insight
Fu’adah et al. (2020)[1]	CNN with 3 hidden layers, 3x3 filters	Achieved 99% accuracy for skin cancer and benign tumor
Shetty et al. (2022) [2]	CNN with carefully selected parameters	Customized CNN with high-performance architecture
Jayalakshmi & Kumar (2019)[3]	Batch Normalized CNN (BNCNN)	Achieved 89.30% accuracy in categorization of dermoscopic images into benign or malignant skin lesions
Salian et al. (2020) [4]	MobileNet Pretrained Model	Achieved accuracy rates of 81.52% without augmentation and 82% with augmentation.
Junayed et al. (2021) [5]	GoogleNet, MobileNet, Custom CNN	Compared performance of pretrained models against custom CNN models.
Hassan et al. (2020) [6]	DenseNet-121	Used DenseNet-121 with data augmentation for classifying skin lesions.
Sae-Lim et al. (2019) [7]	MobileNet	Demonstrated MobileNet's efficiency in classifying skin lesions.

Dataset Description

- **Dataset Name** – HAM10000 dataset
- **Dataset Source**- Kaggle
- **Number of Attributes**- 7 Attributes
- **Number of Instances-** 10015 Instances(Each instance in the dataset provides relevant information about the skin lesion)
- **Number of Images-** 10015
- **Number of Classes-** 7 classes of skin lesion

Database Description

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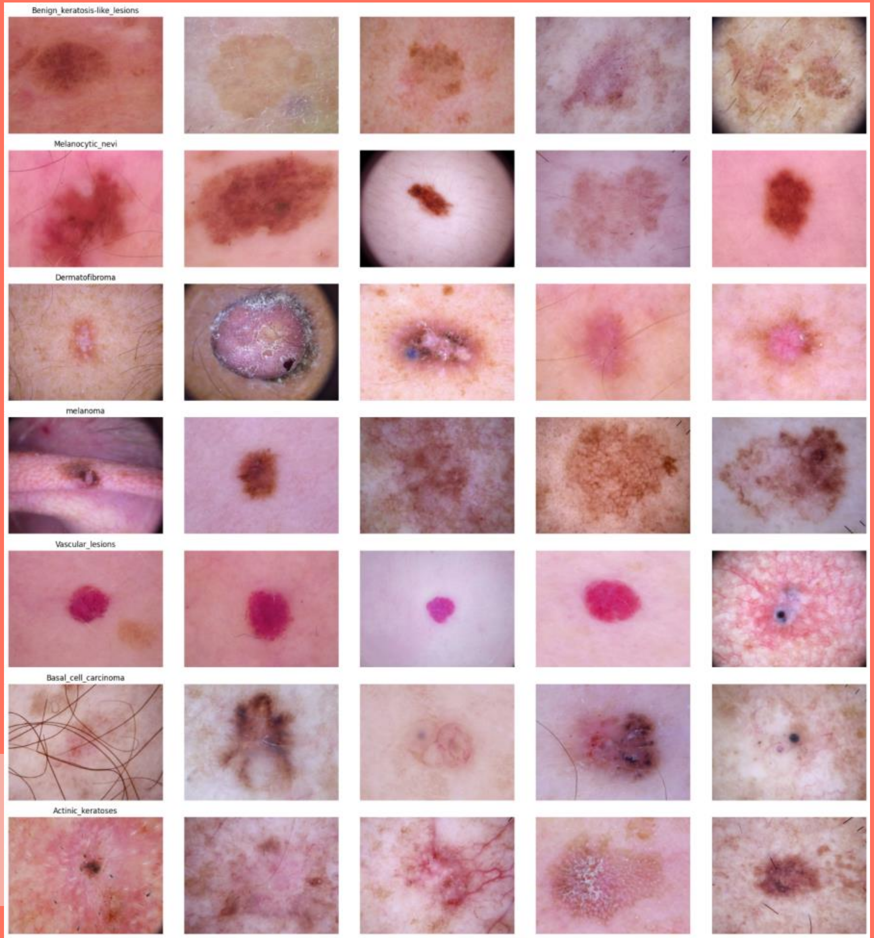
Attribute	Description
lesion_id	A unique identifier for each lesion.
image_id	A unique identifier for each dermatoscopic image in the dataset.
Dx	The diagnostic category of the skin lesion. Categories include Actinic keratoses and intraepithelial carcinoma (akiec), basal cell carcinoma (bcc), benign keratosis-like lesions (bkl), dermatofibroma (df), melanoma (mel), melanocytic nevi (nv), and vascular lesions (vasc).
dx_type	The method of lesion diagnostic used. It specifies whether histopathology (histo), follow-up examination (follow_up), expert consensus (consensus), or in-vivo confocal microscopy (confocal) confirm the diagnostic category (dx).
Age	The patient's age at the time the image was taken.
Sex	The gender of the patient.
localization	The specific location on the body where the skin lesion is located.

Skin Lesion Classes



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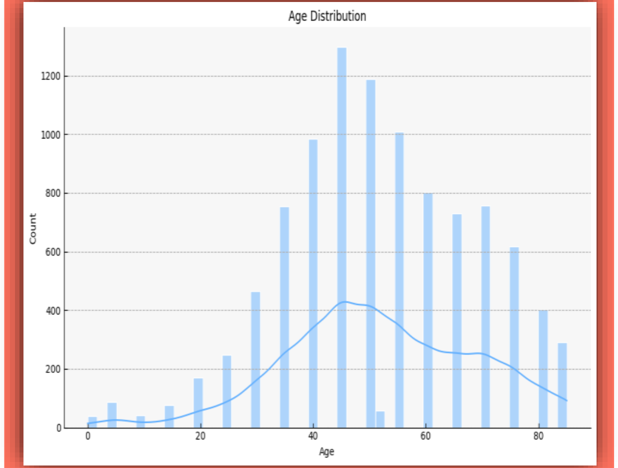
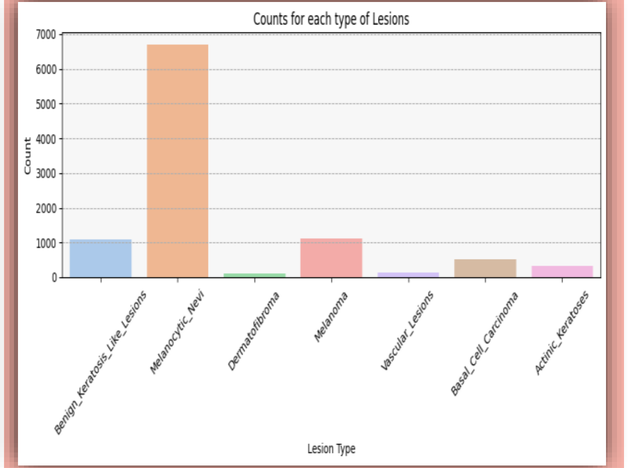
- Benign Keratosis Like Lesion
- Melanocytic Nevi Lesion
- Dermatofibroma Lesion
- Melanoma Lesion
- Vascular Lesion
- Basal Cell Carcinoma Lesion
- Actinic keratoses and intraepithelial carcinoma

Exploratory Data Analysis

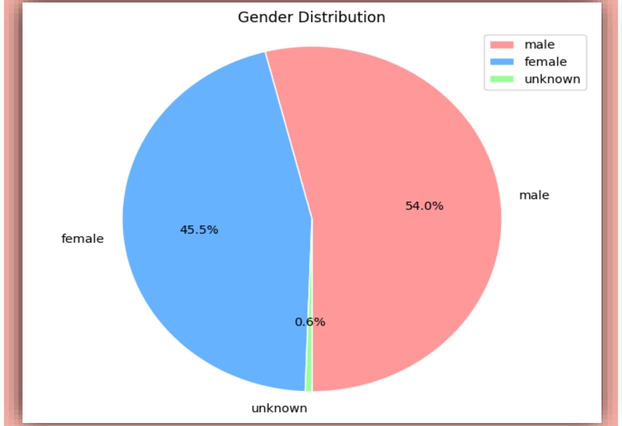
1. Age Distribution



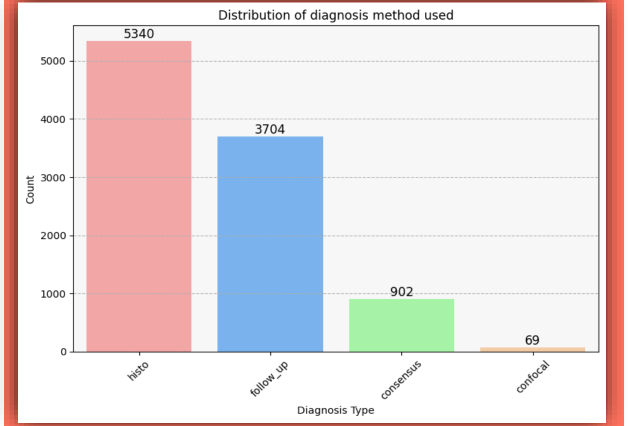
3. Seven Classes of Skin Lesion



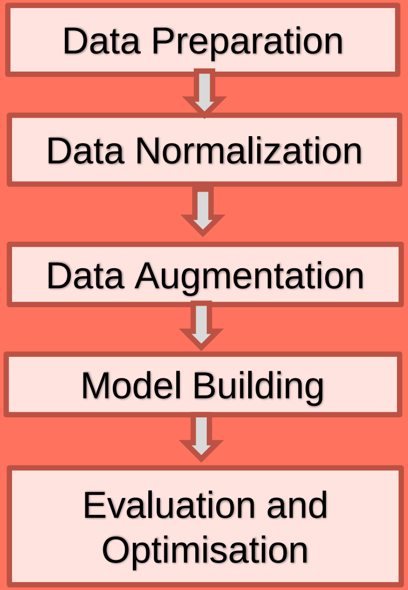
2. Gender Distribution



4. Diagnosis Method



System Design



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Step1: Data Preparation- It will be carried out resizing image data, Splitting dataset.

Step2: Data Normalization- This procedure involves transforming image pixel values to a standardised scale

Step3: Data Augmentation- This step applies several transformations to current data samples to produce new, slightly changed sample.

Step4: Model Building- In this critical step, we embark on constructing the different models of our skin lesion detection system.

Step5: Evaluation- This step will evaluates the effectiveness and accuracy of the built models. Also, performs model optimization.

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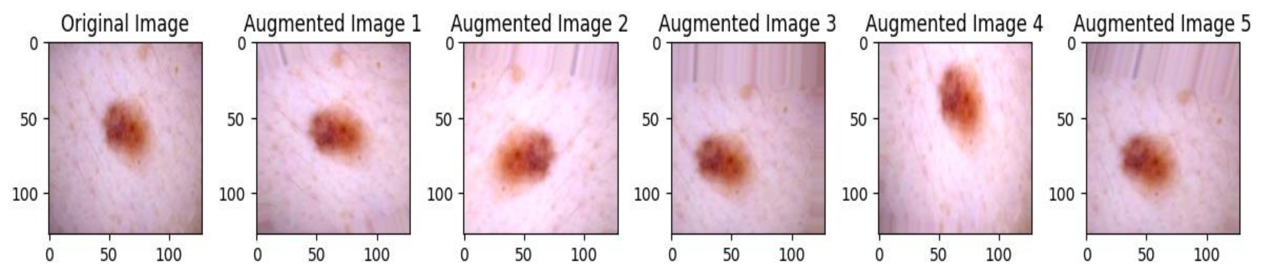
Data Augmentation

- Data augmentation is a technique used in deep learning for artificially boosting the diversity of a dataset by performing various transformations to the existing data.
- Data augmentation approaches were used to balance underrepresented classes.
- This approach not only expands the dataset but also strengthens the model's capacity to adapt to various conditions

Augmentation Parameters

```
#augmentation parameters
rotation_range = 20
width_shift_range = 0.2
height_shift_range = 0.2
shear_range = 0.2
zoom_range = 0.2
horizontal_flip = True
brightness_range = (0.8, 1.2)
```

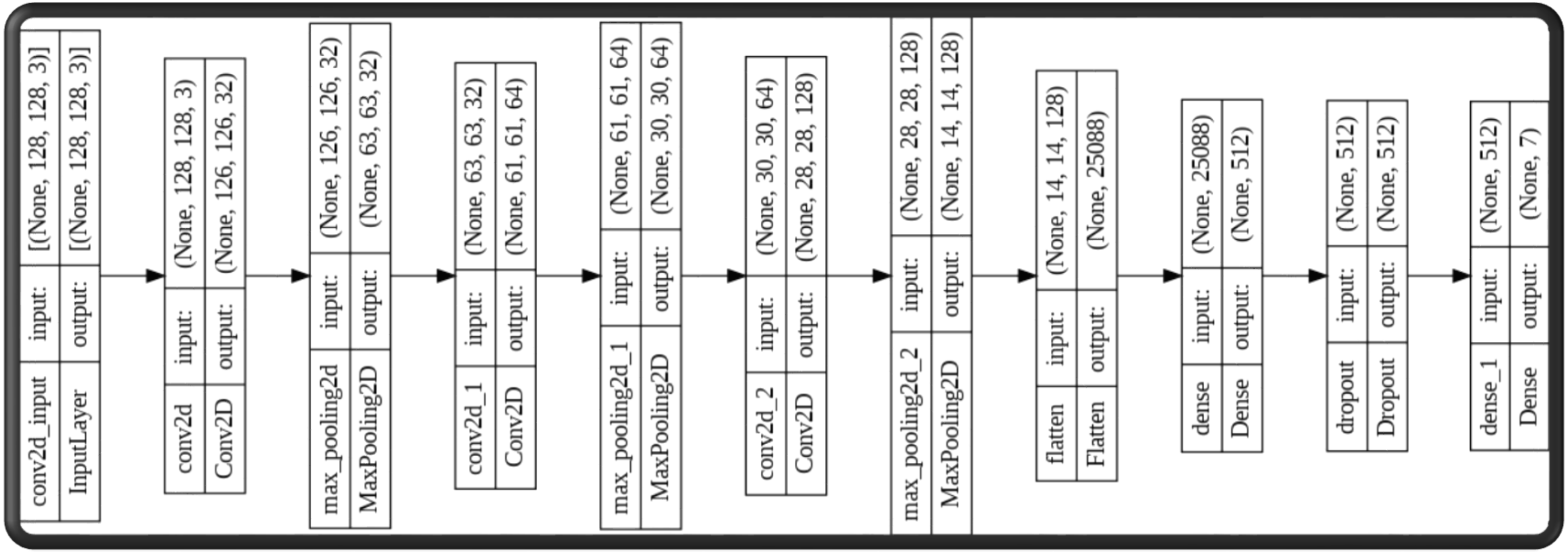
Example



CNN Architecture

- **Convolutional Layers:** The CNN architecture is made up of three convolutional layers, each of which employs 3x3 filters to detect local patterns in input skin lesion pictures.
- **Max-Pooling:** Following every layer of convolution, there's a max-pooling layer that gradually decreases spatial dimensions to capture vital features at various scales.
- **Flatten Operation:** After convolutional layers, a flatten operation turns 2D feature maps into a 1D vector for fully connected layers.
- **Dense Layers:** To capture abstract picture representations, the model incorporates a dense layer with 512 units and ReLU activation.
- **Dropout:** To reduce overfitting, a 0.5 rate dropout layer is utilised, randomly deactivating neurons during training.
- **Final Dense Layer:** The architecture concludes with a dense layer having seven units, corresponding to skin lesion classes. It assigns class probabilities via softmax activation, resulting in a multi-class classification output.

CNN Architecture Diagram

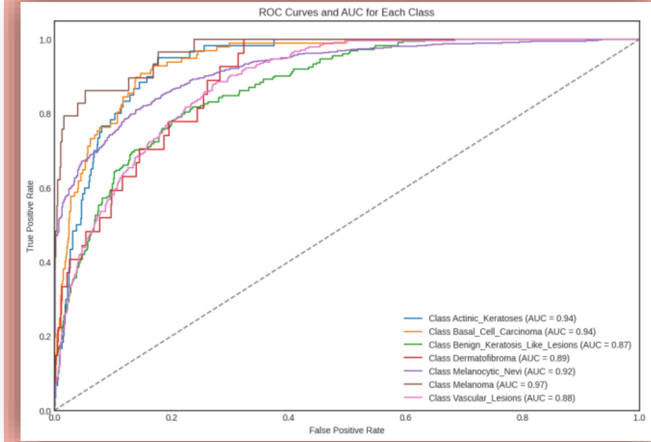


CNN model Performance

- **Test Accuracy-** 74.79%
- **Test Loss-** 0.6426

- **Validation Accuracy-** 76.93%
- **Validation Loss-** 0.6324

Confusion Matrix



ROC Curve and AUC

Transfer Learning Approach and Models

- **Transfer Learning:** Using pre-trained neural network models for new tasks.
- **Advantages:** Speeds up training and improves performance, especially with minimal data.

Approach 1: Feature Extraction

- Use pre-trained model as a fixed feature extractor.
- Remove the uppermost layers.
- Add new layers for the skin lesion detection task.
- During training, just the weights of the new layers are updated.

Approach 2: Fine Tuning

- Fine-tune the entire pre-trained model.
- Unfreeze some or all layers.
- Continue training with a lower learning rate.
- Suitable for bigger datasets.

Pretrained Models Used

- **VGG16 Model**
- **MobileNet Model**
- **DenseNet121 Model**
- **InceptionV3 Model**
- **ResNet50 Model**

Model Performance

	Baseline CNN	VGG16 Fine Tuned	MobileNet Fine Tuned	DenseNet Fine Tuned	InceptionV3 Fine Tuned	ResNet-50 Fine Tuned
Test Accuracy	74.79%	75.73%	83.23%	78.63%	75.88%	72.24%
Test Loss	0.6426	0.704	0.561	0.584	0.616	0.7754
Validation Accuracy	76.93%	72.31%	81.80%	73.79%	79.30%	71.94%
Validation Loss	0.6324	0.736	0.608	0.718	0.573	0.7950

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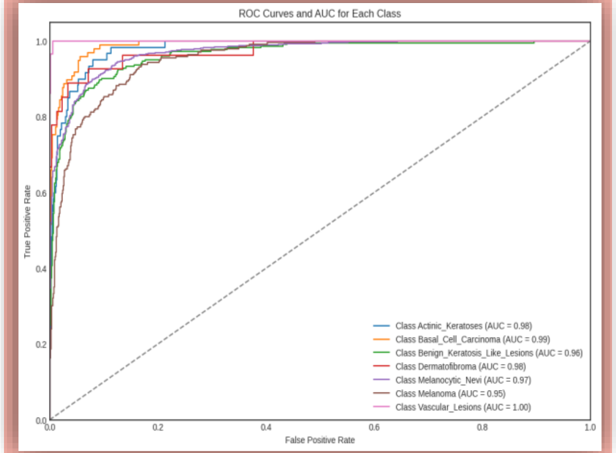
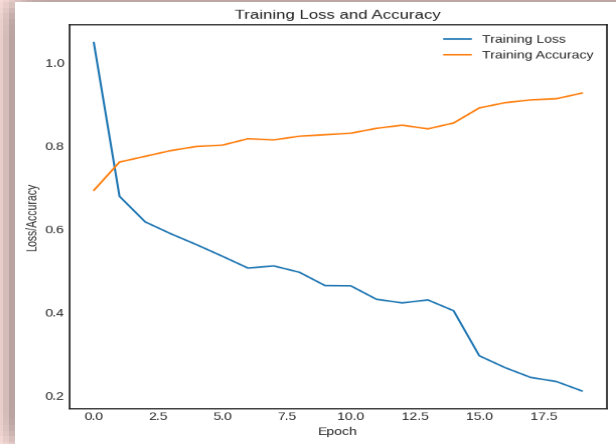
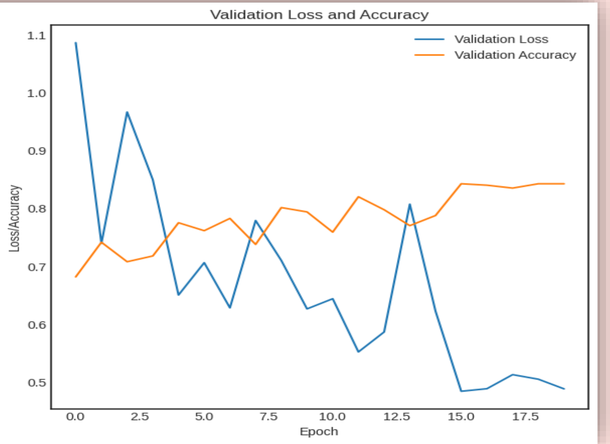
Optimised MobileNet Model







Optimization Strategy-

- Setup callbacks
- Adding Batch Normalization Layer

Accuracy- 87%

Classification Report of Optimised MobileNet Model

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	Precision	Recall	F1-score	Support
Actinic Keratoses	0.74	0.57	0.64	60
Basal Cell Carcinoma	0.88	0.74	0.80	97
Benign Keratosis Like_Lesions	0.72	0.80	0.76	224
Dermatofibroma	0.68	0.78	0.72	27
Melanocytic Nevi	0.91	0.96	0.94	1320
Melanoma	0.80	0.56	0.66	246
Vascular Lesions	0.90	0.90	0.90	29
Accuracy	0.87			2003
Macro avg	0.80	0.76	0.77	2003
Weighted avg	0.87	0.87	0.86	2003

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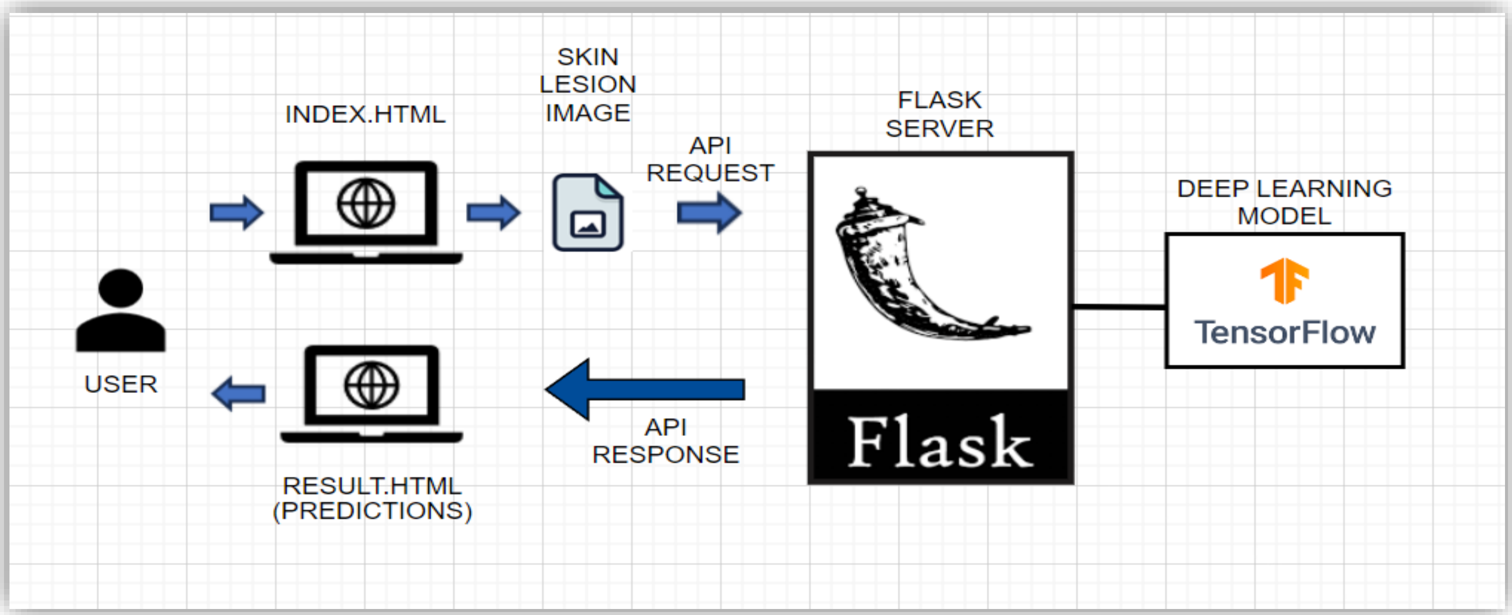
Web App Development using Flask Framework



Web App Demonstration 1

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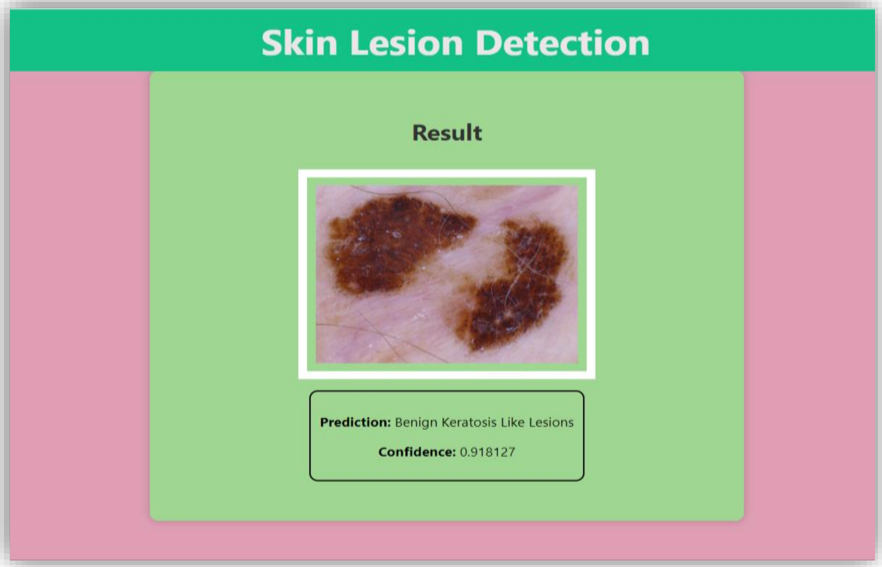
Uploading Skin Lesion Image

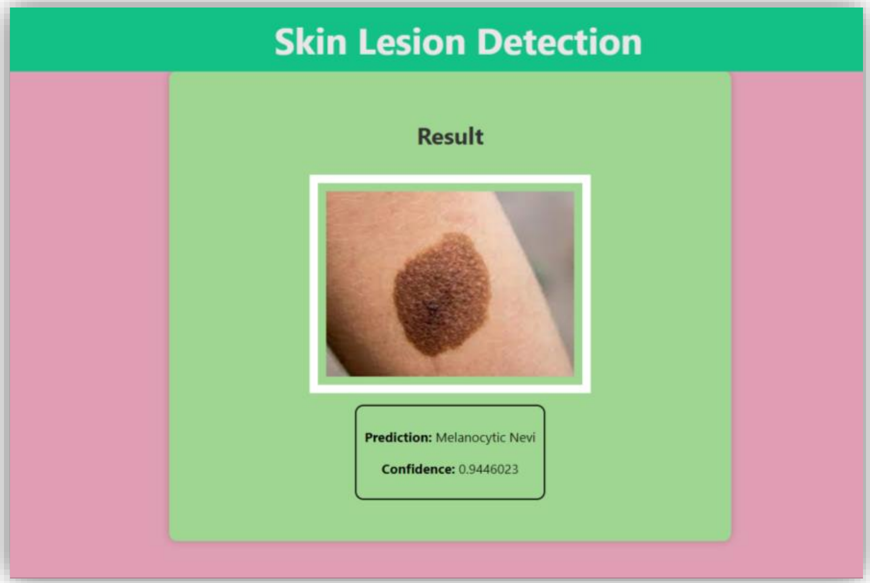
Output of Uploaded Skin Lesion Image



Web App Demonstration 2

Paste Skin Lesion Image URL

Output of provided Skin Lesion Image URL



Discussion

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Baseline CNN

The designed CNN with only 10 layers performs admirably in identifying skin lesions.

Transfer Learning

According to the results of the study, the transfer learning model with fine-tuning strategy outperformed the feature selection method.

Parameters

The parameter settings of the models were maintained in accordance with one another to guarantee a fair assessment of model performance.

MobileNet Model

Optimized MobileNet achieved an exceptional 86.96% accuracy, exceeding prior studies, including those using MobileNet.

Limitations

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- Data imbalance, a typical problem that is especially prominent in medical datasets, was observed in the research.
- Model performance was impacted by data skew, which made it difficult to categorize minority groups appropriately.
- While the dominant class (Melanocytic Nevi) had great performance, minority groups displayed different degrees of accuracy.
- The limited computing resources made it difficult to develop more complicated models or carry out prolonged training, which had an impact on training time and model complexity.

Conclusion and Future Work

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- Our work demonstrates the potential of deep learning methods in the detection of skin lesions.
- We developed a 10-layered CNN architecture and tested five transfer learning models.
- MobileNet emerged as the best performance, with impressive accuracy, recall, F-score, and AUC.
- We proposed optimisation tactics such as callbacks and batch normalisation, which dramatically increased MobileNet's accuracy to 87%.
- Recommend experimenting on a more diverse set of skin lesions, including those with different complexion tones and ethnic backgrounds.
- Explore methods like adaptive sampling and ensemble learning to enhance model performance.
- Use cutting-edge technology to build increasingly complex models, such as TPUs and edge computing devices.

THANK YOU

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