Skin Cancer Classification using CNN

Abstract

The project's goal is to improve skin cancer early detection by using fast and precise image classification. Our experiment involved skin cancer images dataset obtained from Kaggle.com. We have evaluated five Convolutional Neural Networks (CNN) models which undergo iterative improvements, incorporating techniques such as data augmentation and regularization to address overfitting and enhance generalization. The projects' methodology follows the Cross-Industry Standard Process for Data Mining (CRISP-DM), providing a structured approach to data analysis and model development. The report provides a full analysis of the models' performance, evaluation measures, and adjustments. Final models accuracy reached 0.60%, showed effective learning from augmented data, model was efficient in training and resilient to overfitting. Study also found dataset size could have influence on model accuracy as well as the images' lack of variety in skin tones leading to data bias. The observations align with previous research, which has shown issues, including partial labeling, biases in the dataset, and challenges in applying results to clinical settings.

1. Introduction

Skin cancers are globally recognized as the most common types of cancers, reaching an astonishing estimate of over 1.5 million new cases in 2020 alone[1].

The key to fighting skin cancer is early detection, which emphasises the vital significance of quick and effective recognition techniques. Skin cancer with its wide range of appearances and tendency for rapid progression, shows how important early detection is to reduce the impact of this disease. There is an urgent need for quick and precise identification techniques as the traditional diagnostic methods can take a long time. This has created a need for advanced technology that can speed up identification without losing accuracy.

The main goal of this paper is to investigate and to assess the efficiency of Convolutional Neural Networks for identification of skin cancer.

We wanted to create a strong tool that can classify images quickly and accurately by using deep learning and image analysis, which will help achieve the important objective of early detection.

In this paper we also review the literature related to identification of skin cancer which will serve as a foundation for our paper. We critically evaluate positive and negative aspects of related work and assess how it can be useful to our work. Examining the challenges and limitations in related literature helps us to make better decisions, prepares us to face new challenges, and helps us learn from previous mistakes.

Also, we introduce Data Mining Methodology which we approached for our objective as well as Deep Learning algorithm which we chose to use for our work. In the upcoming stages of our research, we conduct an evaluation of the accuracy of our selected methodology and its effectiveness. We summarise our findings to assess accuracy , insights and effectiveness of our approach.

2. Related Work

Over the years, a number of methods for categorising and classifying skin cancer cases have been developed. In 2017 at Skin Imaging Challenge[2] authors suggested different approaches. The challenges focused on improving automated melanoma diagnosis in problems related to segmentation, detection of dermoscopic features, and classification. Limitation of the study found dataset bias and partial labeling of dermoscopic features.

Published in 2018 [3], the study also aimed to create an artificial trained system that can classify skin diseases into multiple categories including healthy skin, acne, eczema, benign, and malignant skin tumors. The research used CNN with pre pre-trained ”AlexNET” model for feature extraction, after applying SVM classifiers they achieved 86.21% accuracy. One of its limitations was that it didn't investigate how data - balancing affects the classification.

Work published in 2017[4] suggested combining CNN and RNN to improve segmentation accuracy. The proposed method was tested on publicly available metrics for dermatology image analysis. Design used seven convolutional layers and two max pooling layers followed by two recurrent layers with direction-coupled horizontal and vertical sweeping functions. This method achieved high accuracy of 0.98% on images from ISIS 2019 but there were limitations of this method as model performance was evaluated on specific dataset raising questions about data diversity with different learning conditions.

In 2019 in a paper published by SITIS [5] authors suggested combining CNN with GNN(Gabor Filtering). Proposed model was designed to extract spatial information including ages and textures. The results on images from ISIC 2019 dataset shown 96.39% accuracy but there are some limitations like generalisation of the dataset and absence of validation in clinical setting.

Another publication from the same year focused on CNN method and addressed the issue of limited annotated data by employing Generative Adversarial Network GAN to generate synthetic data[5]. The main dataset came from the International Skin Imaging Collaboration (ISIC) and included 97 subjects (50 benign and 47 malignant). The model performance without synthetic images was 53% but with addition of synthetic images performance was better at 71%. With such a good performance there were also limitations concerning possible biases caused by GAN algorithm, the applicability of synthetic images to real-world scenarios and the need for further validation on diverse datasets and clinical settings.

Another work from 2019 [6] introduced CNN for early skin cancer detection archiving 89% accuracy on data from skincheckup.online. Software aimed to allow users to identify skin tumors by processing images in accordance with ABCDE symptoms complex used also in clinical trials. The paper highlighted the importance of early diagnosis but didn't discussed challenges where the development system may not perform optimally.

The work from 2020 [7] investigated the use of MobileNet v2 and Faster R-CNN for skin cancer detection via an Android-based application that makes use of smartphone cameras. This work highlighted early cancer detection through widespread use of smartphone technology. Authors used 600 images for training and testing using MobileNet v2 and Faster CNN models. Two approaches were used in the testing phase: Jupyter notebooks and a smartphone camera. The findings shown that Faster R-CNN performed more accurately than MobileNet v2, with the first one obtaining 87.2% accuracy in Jupyter testing. However, when tested with the Android app, MobileNet v2 achieved the same high accuracy (86.3%). Authors suggested that future work could involve incorporating segmentation methods to further improve accuracy.

In work from 2021 [8] the authors suggested a two-step procedure: first, classifying the type of skin lesion by applying the gained information to Mask R-CNN model, and then using a Mask R-CNN model for recognising and outlining skin lesions. In the result method worked well, achieving 98% accuracy indifferent metrics like Jaccard Index and Dice Coefficient. Also, it performed great in classifying types of skin tumor. The limitations rose regarding not enough data, imbalance in types of skin condition as well as need for better machines and their capacity. The authors also were not sure if the method would work on other kinds of images then skin images, like clinical photos.

In the same year, work published in CIBCB presented a 2D-CNN model based on EfficientNet on a dataset of 10351 images[9]. In this experiment, a picture preprocessing process that includes image augmentation, image conversion, and image resizing was carried out before the model was fed. By adjusting the scale coefficients, the model was modified to better fit the training dataset and the model obtained 98% accuracy in the ISIC dataset. The authors observation from this experiment was that picture pre-processing had a significant influence on image-based categorization tasks. Authors summarised that the proposed model cannot achieve such high accuracy without image pre-processing.

In the study from 2021 [10], The author's advocated approach used parallel convolution blocks to efficiently capture distinctive characteristics of skin cancer. The model performed remarkably well in classification and it outperformed CNN designs like VGG-16 and VGG-19. In order to achieve good training outcomes, data augmentation techniques were used to satisfy the requirement for extensive data requisition. The exploratory analysis shown significant improvements in precision (76.16%), recall (78.15%), and F1 scores (76.92%). The study promoted complex approaches like Belief Rule Based Expert Systems (BRBES) to address uncertainty in the classification process. At the end the authors proposed an extensive review of various data collections to improve the model's validation and stability as well as suggesting different CNN models such as ResNet, DenseNet, and InceptionNet to be investigated.

In 2022 work published by SMART[11], the authors used CNN and SVM algorithms which presented great results highlighting CNN's dominance in terms of accuracy and precision (95.03%) over SVM accuracy of 94.04% .Both algorithms were tested on a sample of 20 images. That meant the results may not be applicable due to the limited sample size and potential lack of age group representation. Although the CNN algorithm performed better, there were no details in the paper about clinical validation of the data.

Also, in 2022 work published by INSECT [12] used CNN and HAM10000 dataset. The model implemented the KERAS and Tensorflow framework, achieving accuracy of 85% dividing skin tumors into groups, like malignant melanoma, basal cell carcinoma, and actinic keratosis. This work's limitations involved its reliance on a rather small dataset of 10,015 which may limit the generalizability of the model as well as the models accuracy is influenced by a presence of diverse dataset. Authors in this work focused attention on future study which should look into ways to improve accuracy by obtaining better dataset while cutting costs and training time.

3. Methodology

As the foundation of our research project, we have selected the Cross-Industry Standard Process for Data Mining (CRISP-DM) for our investigation into the effective detection of skin cancer using Convolutional Neural Networks (CNNs). CRISP-DM offers a strong and methodical structure that directed our investigation through specific phases that closely correspond with our goals.

The selection of CRISP-DM resulted from its flexibility in handling a wide range of data mining tasks and its focus on iterative processes. Skin cancer classification includes extensive image processing and pattern recognition. The structured method of CRISP-DM provides a thorough investigation of the problem space, from analysing the data to implementing and evaluating models.

The CRISP-DM major phases—Business Understanding, Data Understanding, Data Preparation, Modelling, Evaluation, and Deployment—as illustrated in Figure 1 are especially appropriate for our study goals. We were able to methodically go forward from problem definition and comprehension of the complexities of skin cancer data to preparing and transforming the data for CNN model training.

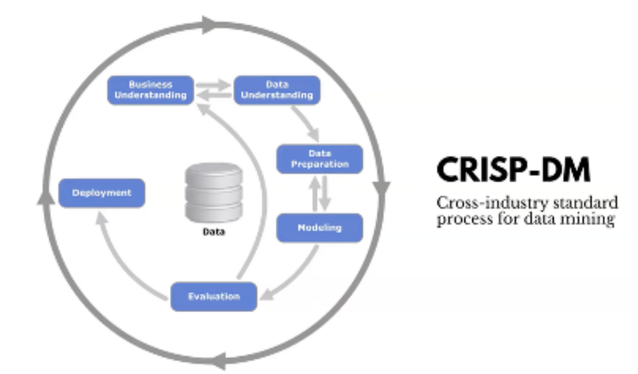

Figure1. CRISP-DM process [13].

We intend to present comprehensive analyses of every stage of the CRISP-DM process in relation to our skin cancer classification study in the parts that will follow. We discuss the reasoning behind our decisions, the difficulties we faced, and the adjustments we did to accommodate the complexities of skin cancer diagnosis. This extensive methodology serves as the foundation for our investigation, resulting in a detailed assessment of the accuracy and effectiveness of our CNN-based approach.

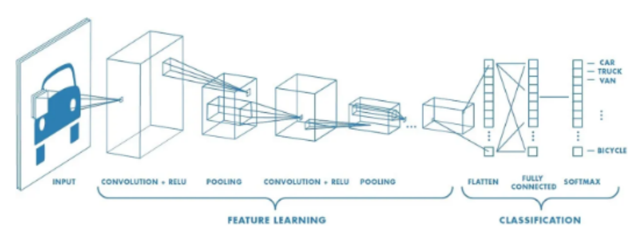

Figure 2. Convolutional Neural Network [14].

4. Evaluation

- **Data Collection**

We used the *"Skin Cancer ISIC "*dataset from Kaggle for our study on skin cancer classification. The images in the dataset include both benign and malignant oncological diseases. The International Skin Imaging Collaboration (ISIC) provided these specially selected photos. **Actinic keratosis, Basal cell carcinoma, Dermatofibroma, Melanoma, Nevus, Pigmented benign keratosis, Seborrheic keratosis, Squamous cell carcinoma, and Vascular lesion** are among the skin conditions included in the dataset. This varied collection guaranteed a representative sample for our research.

Pre-processing for the Kaggle dataset was not necessary because it wasn't missing any data and was well-structured. It was initially split into training and testing sets, which we combined to create a single dataset containing 2357 images. Each folder was labelled with its corresponding skin disease class, offering a balanced representation across categories. The simplified dataset made it easier to integrate into our analysis.

The Kaggle skin cancer dataset was selected based on how well it matched our goal of creating a CNN-based skin cancer detection model. The origins of the dataset: The International Skin Imaging Collaboration, with its richness in a variety of skin diseases, highlights its application and relevance to real-world situations. We discuss our deep learning approach to skin cancer classification in detail in the following sections, which include our model architecture, training process, and evaluation metrics.

- **Exploratory Data Analysis (EDA)**

We used EDA in the first phase of our skin cancer classification research to understand the characteristics of the dataset. Nine different forms of skin cancer are represented by the 2357 images in the dataset, as previously explained. Sample images for each type, which are displayed in Figure 3, were visually examined to provide an idea of the diversity of the dataset. These graphics give a sneak peek at the complex nature of the dataset, help in understanding the distinct characteristics of each class and serve a foundation for developing effective classification models.

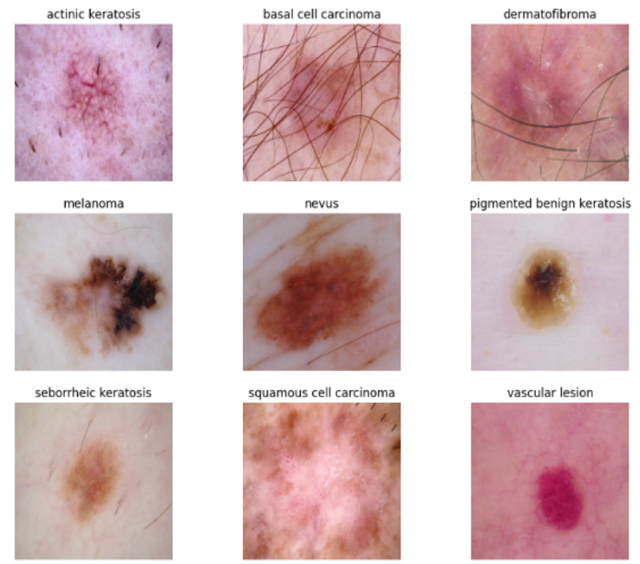

Figure 3. Sample images for each skin cancer type.

We concentrated on data exploration and class distribution analysis in the next step. The distribution of the various skin diseases in our dataset, as seen in Figure 4 and 5, was revealed by this study, offering important new information for the training and assessment of the model in the future.

Label	Count	Percentage
pigmented benign keratosis	478	20.280017
melanoma	454	19.261773
basal cell carcinoma	392	16.631311
nevus	373	15.825202
squamous cell carcinoma	197	8.358082
vascular lesion	142	6.024608
actinic keratosis	130	5.515486
dermatofibroma	111	4.709376
seborrheic keratosis	80	3.394145

Figure 4. Distribution of different skin cancer types in our dataset.

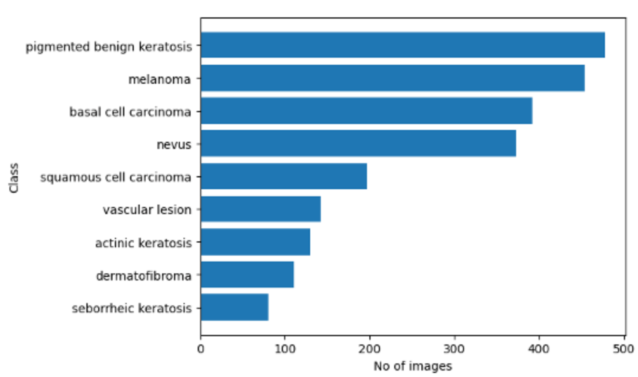

Figure 5. Graph of different skin cancer types in our dataset.

In our dataset, pigmented benign keratosis accounted for 478 cases, was the most common class, while seborrheic keratosis had the lowest representation, with only 80 cases.

- **Feature Engineering**

The goal of our skin cancer classification study was to create a robust model that could accurately identify different skin diseases from photos. The methodology included important components such as feature engineering, model building, and training, each specifically designed to address issues with class distribution and maximise overall performance. Feature engineering was essential in getting our image dataset ready for efficient modelling. To ensure compatibility with neural network input, rescaling RGB channel values to the [0, 1] range was part of the standardisation process.

In addition to standardisation, one significant improvement was the addition of data augmentation methods. **Data augmentation** is a powerful method for improving model generalisation. By adding random alterations to the training dataset, it encourages the production of a wide range of sample sets. These transformations, including zooms, rotations, and horizontal flips, help the model learn robust features and patterns that are resistant to such changes. The goal is to prevent the model from memorizing specific features of the training data, encouraging it to learn the underlying patterns. With more variants introduced, the model should be better able to generalise to new, untested data.

- **Model Architecture, Training and Results**

MODEL 1

Model 1 was the first version of our Convolutional Neural Network (CNN) architecture that we developed for our skin cancer categorization study. Model 1 served as our baseline and included key layers for effective picture classification, such as dense layers for higher-level reasoning, max-pooling layers for downsampling, and convolutional layers for feature extraction. In order to learn hierarchical characteristics, the standardised input images- achieved by rescaling RGB channel values to the [0, 1] range-passed through these layers. Max-pooling layers reduced the amount of feature maps, dense layers handled higher-level reasoning, and convolutional layers found and retrieved patterns. With the help of this comprehensive architecture established by the combination of various layers, the neural network was able to absorb and learn from the input data, extracting hierarchical features and making informed decisions.

The following are some of our models' layer functionalities:

- **Rescaling Layer**: The RGB pixel values are brought into the [0, 1] range by the rescaling layer, which is in responsibility for standardising the input data. To ensure consistency in the input data and to improve the neural network's ability to learn from the images, this normalisation is essential.

- **Convolutional Layers**: The core components of convolutional neural networks (CNNs) are convolutional layers. Convolution operations are carried out by these layers, which entail using a set of learnable filters or kernels to scan the input image. The network can identify and pick up hierarchical elements like edges, textures, and patterns with the use of these filters. In order to capture spatial relationships within the input data, convolutional layers are necessary.

- **Batch Normalization**: By modifying and scaling the activations of a neural network layer, batch normalisation is used to normalise them. This technique reduces the sensitivity to weight initialization and aids in increasing the pace of convergence during training. Batch normalisation helps to speed up and stabilise the training process by normalising the inputs to a layer.

- **Max-Pooling Layers**: The feature maps generated from convolutional layers are downsampled using max-pooling layers. These layers preserve significant information while reducing the input data's spatial dimensions. Usually, max-pooling is carried out by choosing the highest value from a range of values included in a certain input region. By reducing the size of the feature representation, this downsampling helps the network become more computationally efficient.

- **Flatten Layer**: The multidimensional data obtained from previous layers is converted into a one-dimensional array using the flatten layer. The process of flattening is required while moving from pooling and convolutional layers to dense layers. The data is transformed into a format that can be fed into fully connected layers.

- **Dense Layers**: In a neural network, dense layers—also referred to as fully linked layers—are in charge of high-level reasoning and decision making. Every neuron in a dense layer is linked to every other neuron in the layer before it. These layers are essential for identifying complex connections and patterns within the data. The network can carry out classification or regression tasks thanks to the dense layers, which base their decisions on the features that the preceding layers have learned.

Model 1's validation accuracy was 28.87%, while its initial training over 10 epochs produced a low accuracy of 20.41%. Its performance is shown in Figure 6, and related worries concerning overfitting are revealed in Figure 7, which shows accuracy and loss graphs. The training accuracy peaked at 60.18% in later epochs, but the validation accuracy remained constant at 50.53%. In order to resolve overfitting and enhance overall performance, this underscores the difficulty in achieving consistent generalisation and the necessity of further model upgrades.

```
Epoch 9/10
59/59 [==============================] - 68s 1s/step - loss: 1.1503 -
accuracy: 0.5954 - val_loss: 1.5484 - val_accuracy: 0.5074
Epoch 10/10
59/59 [==============================] - 67s 1s/step - loss: 1.1144 -
accuracy: 0.6018 - val_loss: 1.5084 - val_accuracy: 0.5053
```

Figure 6. Model 1 Training and Validation Accuracy.

Figure 7. Model 1 Training & Validation Accuracy and Loss.

Data Augmentation
We implemented data augmentation methods to improve next models capacity for generalisation. Random transformations like rotations, zooms, and horizontal flips are all part of the augmentation. Analysing the enhanced photos, as displayed in Figure 8 and 9, revealed details on the variety added to the training set.

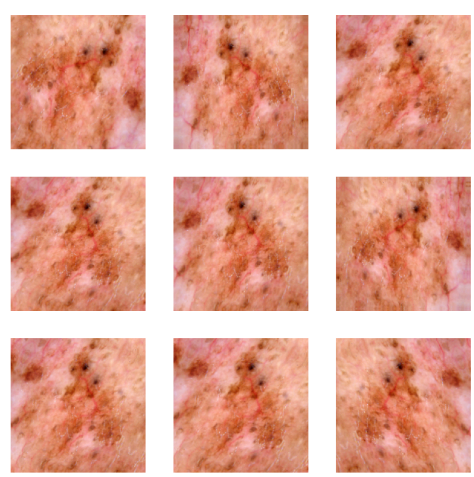

Figure 8. Variety of images added to training set.

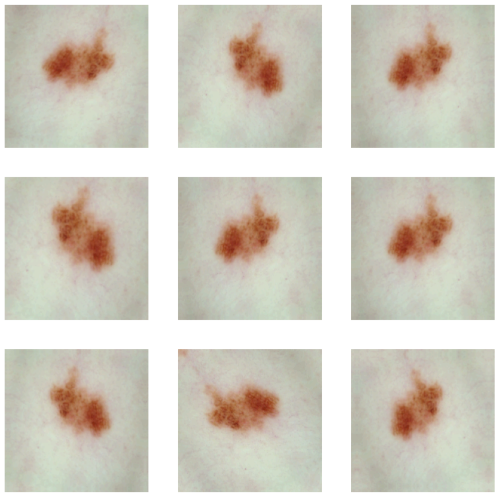

Figure 9. Variety of images added to training set.

MODEL 2

The architecture of Model 2, featuring data augmentation, rescaling, convolutional layers, max-pooling layers, dropout for regularization, and dense layers, showed promising results after 15 epochs of training. The accuracy and loss plots demonstrated improved performance, indicating that data augmentation effectively reduced overfitting observed in Model 1. Validation accuracy increased from 36.52% to 54.56%, whereas training accuracy began at 23.97% and ended at 58.70%. These outcomes signify improved learning capacity and generalization, setting the stage for further improvements in subsequent iterations.

```
Epoch 14/15
59/59 [==============================] - 83s 1s/step - loss: 1.1704 -
accuracy: 0.5838 - val_loss: 1.3465 - val_accuracy: 0.5478
Epoch 15/15
59/59 [==============================] - 82s 1s/step - loss: 1.1187 -
accuracy: 0.5870 - val_loss: 1.2957 - val_accuracy: 0.5456
```

Figure 10. Model 2 Training and Validation Accuracy.

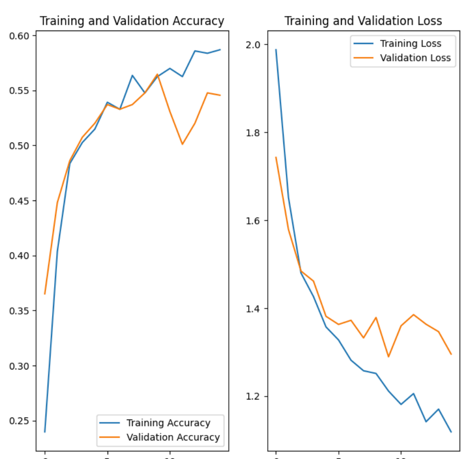

Figure 11. Model 2 Training & Validation Accuracy and Loss.

MODEL 3

Our model 3 was modified to improve performance and address certain issues found in the earlier models. Convolutional layers have been deepened, and further layers have been added to capture more complex features. After every convolutional layer, batch normalisation was used to increase convergence speed and lessen sensitivity to weight initialization. To accommodate the increased complexity of the network, the dense layers were modified, with the first dense layer now having 256 neurons. To further improve generalisation and avoid overfitting, a dropout layer with a rate of 0.3 was incorporated after the initial dense layer for regularisation.

Following 10 training epochs, Model 3's accuracy on the training set was 28.26%, while its validation accuracy was 30.36%. These findings point to a slight improvement in the model's learning ability, but there are clearly challenges in the way of reaching higher accuracy levels. To solve these issues and improve model performance in later iterations, more research and modifications were required.

```
Epoch 9/10
59/59 [==============================] - 221s 4s/step - loss: 1.9209 -
accuracy: 0.3012 - val_loss: 1.9740 - val_accuracy: 0.2696
Epoch 10/10
59/59 [==============================] - 222s 4s/step - loss: 1.9152 -
accuracy: 0.2826 - val_loss: 1.8999 - val_accuracy: 0.3036
```

Figure 11. Model 3 Training and Validation Accuracy.

Figure 12. Model 3 Training & Validation Accuracy and Loss.

MODEL 4

A number of significant changes were implemented during the Model 3 to Model 4 transition in order to address issues that were found and improve overall performance. Notably, the number of neurons in the first dense layer was lowered to 128 and a second dense layer consisting of 64 neurons was added. Following each dense layer with an increased rate of 0.5 were carefully positioned dropout layers, which are essential for regularisation. In addition, the architecture may have been made simpler by eliminating the batch normalisation stages. By simplifying the architecture, increasing dropout to improve regularisation, and lowering model complexity, these modifications seek to address the overfitting problems found in Model 3. The iterative nature of these modifications indicates a deliberate process of improvement based on problems and observed outcomes, with the aim of improving generalisation and accuracy.

We noticed a changing performance during the course of Model 4's 20 training epochs. From 18.77% to 57.05%, the model's accuracy on the training set grew steadily. On the other hand, there were variations in the validation accuracy, which ranged from 16.77% to 51.17%. Effective learning and pattern recognition are indicated by a decrease in training and validation loss (from 2.16 to 1.27 for training loss and from 2.01 to 1.37 for validation loss).

```
Epoch 19/20
59/59 [==============================] - 162s 3s/step - loss: 1.3546 -
accuracy: 0.5403 - val_loss: 1.3636 - val_accuracy: 0.5499
Epoch 20/20
59/59 [==============================] - 153s 3s/step - loss: 1.2679 -
accuracy: 0.5705 - val_loss: 1.3739 - val_accuracy: 0.5117
```

Figure 13. Model 4 Training and Validation Accuracy.

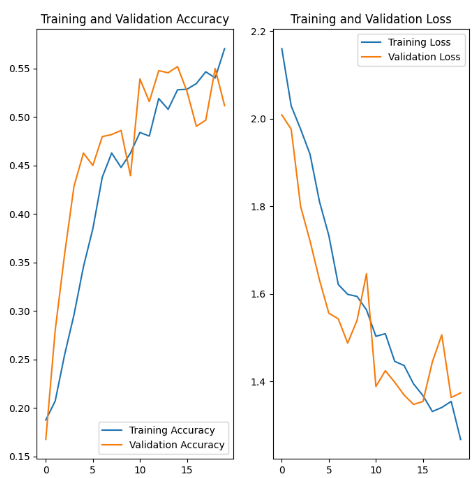

Figure 14. Model 4 Training & Validation Accuracy and Loss.

MODEL 5

The performance of Model 5 was notably influenced by the incorporation of an enhanced data augmentation layer, leading to significant improvements in accuracy and learning capacity. The data augmentation strategy, which included random zoom (set at 0.2), random rotation (adjusted to 20 degrees), and horizontal flipping, introduced additional variations to the training set. Over the course of almost 20 epochs, Model 5 exhibited substantial enhancements in validation metrics and accuracy. Starting with a training accuracy of 18.88%, the model progressively improved to 46.87%, showcasing a substantial advancement over Model 4. The validation accuracy similarly increased from 21.87% to 48.83%, indicating enhanced generalization to previously unseen data. The loss curves demonstrated a consistent downward trend for both training and validation, affirming effective learning. Notably, the performance of Model 5 underscored the advantages of leveraging augmented data, resulting in a more robust and comprehensive skin cancer classification model. This augmentation-driven improvement in accuracy and generalization sets Model 5 apart from its predecessors, highlighting the critical role of meticulous data preprocessing in enhancing convolutional neural network performance.

```
Epoch 19/20
59/59 [==============================] - 164s 3s/step - loss: 1.5637 -
accuracy: 0.4592 - val_loss: 1.4602 - val_accuracy: 0.4947
Epoch 20/20
59/59 [==============================] - 176s 3s/step - loss: 1.5547 -
accuracy: 0.4687 - val_loss: 1.5003 - val_accuracy: 0.4883
```

Figure 15. Model 5 Training and Validation Accuracy.

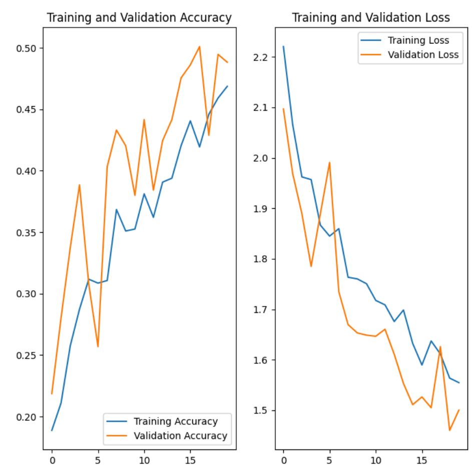

Figure 16. Model 5 Training & Validation Accuracy and Loss.

The process of creating five CNN models to classify skin cancer revealed both advancements and difficulties. Our first model, which served as our baseline, was only somewhat accurate, which led to improvements in following models, such as the addition of regularization and data augmentation methods. Overfitting was effectively handled by Model 2, which included data augmentation, but it also identified areas that needed more improvement. The network's complexity increased with Model 3, which also had difficulties with generalization, especially with validation data. Model 4 achieved an accuracy of 57.05 with changed dropout rates and a simpler architecture; however, consistent generalization was still difficult to achieve. Model 5, which used advanced data augmentation, demonstrated significant gains in accuracy during both training and validation, confirming the effectiveness of these methods. Our process was iterative, which indicated areas for improvement and underscored the significance of addressing overfitting and generalization issues in skin cancer classification models.

Notably, the dataset size constraint remained one of the ongoing issues despite these developments. It was impressive to see such diversity with 2357 photos that showed a range of skin problems; however, the small size made it difficult to reach higher precision. A bigger dataset would probably result in more reliable model training and greater accuracy, given the complex nature of classifying skin cancer. Though the accuracy levels achieved are encouraging, they also suggested that dataset size may have an effect, implying that it may be difficult to achieve accuracy levels above 60% with the available data.

Finally, the essential insights gained from our iterative model development procedure into the intricacies of skin cancer classification are presented. Every model iteration addressed certain issues and improved overall performance. The combining of data augmentation techniques with regularization strategies showed effectiveness in enhancing the generalization capabilities of the models. However, the journey also made clear the fundamental limitations brought on by dataset size. In the future, obtaining and integrating a larger and more varied dataset may be essential to maximizing the potential of skin cancer detection algorithms.

5. Conclusion and Feature Work

In this project we showed the process of creating five CNN models to classify skin cancer cases, we faced obstacles as well as successes in the effort to improve generalisation and accuracy.

One important finding is that the dataset may contain bias because the vast majority of the images were taken of people with white skin tones. This highlights the significance of diversity in datasets in ensuring the accuracy of the training data and raises questions about model's applicability across different skin types.

Our observations are consistent with previous research, which has drawn attention to issues including partial labelling, biases in the dataset, and issues with applying results to clinical settings.

The feature work should concentrate on areas of study including obtaining a much bigger dataset with more skin colour variety as the models will learn more effectively and gain greater accuracy. Also, explore advanced techniques and experiment with different architectures and optimization methods. In the future, these methods can be applied by incorporating our optimized models into a web- or mobile-based platform to accurately self-diagnose skin cancer, helping early detection of this condition, and promoting proactive health.

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