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# Analysis of CNN Models for Melanoma Detection

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**Abstract**

Melanoma is a deadliest type of skin cancer that needs to be detected at its early stages to prevent fatality. Using dermoscopy images of the lesion a computer-based system trained with deep learning will be developed to detect melanoma. The model will identify and categorize melanoma with intricate image processing and classification algorithms, which will be trained on a labeled dataset. Some of the goals of this project is to compile and preprocess a dataset of dermoscopy images labeled with benign lesions and melanoma, evaluate using metrics such as AUC-ROC, accuracy and validation with external datasets, addressing bias while following clinical guidelines. At the end of this research, we hope to improve patient outcomes and lessen the cost of healthcare making it affordable as well as increasing diagnostic accuracy, decreasing false positives and assist dermatologist in early detection of the disease.

**Keywords:** CNN, Computer Vision, Melanoma

## 1 INTRODUCTION

One of the worst forms of skin cancer, melanoma, begins in the melanocytes that make the pigment known as melanin, which gives skin its colour. Melanoma makes up a tiny portion of the skin cancer specimen but due to its high tendency to spread to other regions of the body, it accounts for the bulk of skin cancer related fatalities. The probability to amass melanoma is increased by the factors like history of sunburns, genetic susceptibility and UV exposure. Early detection is important part in dermatology as survival rates are improved by early diagnosis and treatment. Dermatologists visually check to diagnose melanoma using dermoscopic examination which is used as a complement. Dermoscopy referred commonly as epiluminescence microscopy, make it possible to see underlying skin features that are hidden from the naked eye. Though it improves the precision of melanoma detection, the clinician's experience and knowledge remains crucial. Delay of treatment and improper diagnosis results from this subjectivity. Hence, the demand for automated, impartial models helps with timely and precise diagnosis of melanoma.

Preprocessing the dermoscopic images is an important step in creating an automated model. Contrast enhancement and noise reduction are used to raise the image quality while external factors such as camera sensors may blur crucial information in an image. Median filters, Gaussian smoothing and histogram equalization decrease noise and improve contrast in images, and help in improving the visibility of the characteristics of interest. To perform segmentation, techniques such as region-based segmentation, edge detection and thresholding can be employed. CNN has shown considerable results in obtaining accurate segmentation.

After preprocessing, feature extraction is performed to identify and quantify particular lesion features.

Melanoma is identified by finding asymmetry, uneven borders, colour changes and diameter changes. A dataset with all characteristics can be obtained by extracting features, shape detectors and other measurements. Followed by classification where machine learning models like CNN and random forests are used for classifying lesions. Deep learning has attained more recognition due to its ability to extracts useful features without the need for human feature extraction. The model is trained using these algorithms to recognize intricate patterns related to melanoma.
Computer vision and digital image processing offer an objective and systematic method for diagnosis to minimize and mistakes that might come with human assessment. It also has the ability to scan and analyze larger number of samples and detect faster. They facilitate learning and development and allow to be updated with current data to increase accuracy and resilience. Using this technology and models we can create dependable instruments and models that help the medicos to diagnose correctly, hence reducing death rate due to melanoma.

## 2 Literature Survey

In order to assess performance in categorizing skin lesions for melanoma, the paper [1] examines a number of CNN architectures, including DenseNet201, MobileNetV2, ResNet50V2, ResNet152V2, Xception, VGG16, VGG19, and GoogleNet.The authors used a dataset with 7146 deep learning models to reduce training time. They have also pointed out the limitation of the existing systems such as the need for a large dataset and lack of interpretability of the models. They suggest further research is needed to develop explainable models for medical diagnosis and improve performance of the system. Their study offers a thorough analysis to demonstrate the models' potential for melanoma classification.
A framework comprising preprocessing, segmentation, feature extraction, and classification modules is presented in the survey study [2] for the effective and accurate classification of lesions. They claim that FCNN extracts exact ROI and DullRazor removes five hair artifacts. Enhanced SDP extracts feature from ROIs, outperforming ABCD. The authors demonstrate the superiority if their system which combines a stack of RBMs with innovative SDP for categorizing skin cancer. Their model's high accuracy and robustness to datasets make it a promising approach for melanoma detection in coloured skin images.
The authors of the paper [3] want to increase the accuracy of computer-aided diagnosis (CAD) by using a multi-feature fusion framework for skin cancer diagnosis. Their suggested framework includes preprocessing the images using bottom-hat filtering and median filtering to remove artifacts and reduce noise. The lesion is described by calculating HOG and LBP and their extensions. To further categorize melanocytic lesions into nevus and melanoma, the lesion descriptors are supplied into SVM, kNN, and GAB. They use the MED-NODE dataset and 10-fold cross validation to assess their suggested framework and achieved state-of art results thereby presenting a promising approach to melanoma detection using CAD system.
A method for efficiently detecting melanoma is presented in the study [4], which focuses on optimizing a state-of-the-art CNN in order to achieve the best ROC AUC score. In order to train and create models for the 2019 and 2020 IIM ISIC Melanoma Classification Challenges, they looked into a variety of AI clustering methodologies. Using cross-fold validation, the models were assessed; their ROC-AUC score was 99.48%. They demonstrated a potential to develop AI assisted decision support system to augment dermatologists during diagnosis though noting the current GDPR regulations hinder the use of CNN for medical diagnosis. Overall, they present significant contribution to aid medical image processing assisted with AI to diagnose and improve accuracy and efficiency of the melanoma.

Image processing, feature extraction and fusion, feature selection, and classification are the four main processes that the authors of the research [5] have suggested for their deep learning architecture for skin cancer classification. They suggest a brand-new method of contrast augmentation based on knowledge about image brightness. Models that have already been trained Using transfer learning, DarkNet53 and DensNet201 were trained with final residual block modifications. They have applied Genetic Algorithm (GA) to select hyperparameters and thereby fusing the resultant features to approach a two-step named serial harmonic mean. The author and colleagues used Reyni Entropy to choose the optimal features, a process known as marine predator optimization (MPA), and their system performs more accurately than a number of methods. While discussing several challenges faced in segmentation such as low contrast, variations in shape, irregularity, imbalanced skin classes, redundant and irrelevant features, they also provided a detailed comparison with several existing techniques to show their proposed work outperforms.

A paradigm for classifying skin lesions into melanoma, nevi, and seborrheic keratosis is proposed in the paper [6]. They aggregated binary CNNs for melanoma detection using a directed acyclic graph (DAG), drawing inspiration from decomposition and ensemble techniques. They evaluated their method based on ISIC 2018 public dataset and achieved a balanced accuracy (76.6%) among multiclass CNNs using traditional aggregation techniques and other publications. They suggest to develop a reliable and robust automated diagnosis system to classify melanoma. Their hierarchical structure ensures understandable for dermatologists. that CAD is understandable for dermatologists.

The paper [7] presents a computational model for melanoma classification using CNN and ViT with HAM10000 dataset. They have employed mask-guided approaches, creating masks with a specific U2-Net segmentation module. ResNet50, VGG16, and Xception are used by the CNN for transfer learning, and the Bayesian hyperparameter tuner is used to improve training. They also applied gradient weighted class activation mapping achieved an accuracy at 98.37% in Xception and sensitivity of 95.92% and specificity of 99.01%. They assessed the performance using IOU and other metrics. They discuss the limitations of previous studies and addressed them by incorporating XAI technique to bridge the gap thereby presenting a comprehensive study on melanoma.

The paper [8] presents a comparative analysis of various deep learning architectures for melanoma classification using three different datasets, MedNode, OH2 and HAM10000 Kaggle and pretrained models such as AlexNet, VGG16, ResNet50, Inception V3 and GoogleNet. They analyzed the performance using accuracy, sensitivity, specificity, positive predictive value and negative predictive value. Their results show a best accuracy of 97.1%, 97.2% and 96.2% using InceptionV3 for MedNode, PH2 and HAM10000 datasets respectively. They discuss the importance of early detection of melanoma to help reduce mortality rates. They highlighted the challenges in lesion analysis, such as ambiguous boundaries, artifacts, hairs and veins. Additionally, they emphasized how machine learning and deep learning approaches can be used to increase the diagnostic accuracy of melanoma. They discuss related work in the field including use of transfer learning, adversarial learning and ensemble methods for analysis. They highlighted the need for further research in cross domain skin disease recognition and addressing the domain shift issue. Their analysis can help guide future research in this area.

The paper [9] presents a novel deep CNN 10 (DCNN) for accurate classification of malignant and benign melanoma from images. In contrast to other approaches, the authors suggest a lightweight and simpler DCNN by arranging numerous layers for extraction, such as various filters and sizes, using appropriate deep learning layers, deciding on the work's depth, and fine-tuning hyperparameters. Their proposed model achieved a high performance on ISIC 2016, 2017 and 2020 datasets with accuracies of 81.41%,

88.23% and 90.42% respectively. The paper discusses the challenges in skin cancer detection, including scarcity of lesion samples, noise artifacts, among others that makes the classification highly challenging. Their proposed model extracts low to high level information addressing these challenges and offering a solution for classification.
A deep learning-based technique for melanoma classification utilizing a custom CNN in 2023 is shown in the study [10]. Due to the low image quality of the publically available HAM10000 dataset after resizing, the preprocessed data improves the image resolution before being subjected to a deep neural network. They implemented the custom CNN model on the HAM10000 which consisted of seven classes obtaining classification accuracy metrics of 98.77%, 98.36%, and 98.89% for protocols I, II, and III. They compared the results with several models and found theirs to be better than others and to improve performance using various measures they preprocessed using ESRGAN giving a improved 11 picture resolution for smaller images and was trained using the HAM10000 dataset, which included of 10015 images of dermoscopic lesions. Their work is a significant contribution to the field of skin cancer classification using deep learning.

## 3 Methods

The following flowcharts describes the procedures of the six CNN models and to feed data, a data loader was created after dataset extraction following which the models are defined, initialised and training hyperparameters are set. Also several epochs were looped through the training consisting of forward pass, loss computation, backward pass and update of model parameters. Following every epoch, the model is assessed and their accuracy and loss metrics are computed. The performance is visualised by plotting accuracy and loss curves after training, after which the state and model weights are preserved. The watch function is used to visualise the results. The main processes in training and assessing the CNN models are shown in the flowchart, which includes preparation, model definition and initialisation, training, assessment and visualisation. The code trains and assesses ConV, ConV_BatchNorm, ConV_BatchNorm_Dropout, ResNet18, ResNet34 and GoogleNet.

### 3.1 ConV

It is trained using cross-entropy loss and Adam optimiser on dataset while gradients are computed in the backward pass. The output is comoputed in forward pass and loss is identified. They are used to parameters whereas weights and optimiser states are saved at end of each epoch to plot accuracy and loss curves. The watch function is used to visualise based on a batch of data. **Sample Heading (Third Level).** Only two levels of headings should be numbered. Lower level headings remain unnumbered; they are formatted as run-in headings.

### 3.2 ConV_BatchNorm

It uses batch normalisation layers where max pooling layers come after two convolutional layers with batch normalisation and ReLU activation as training stability and speed can be increased using batch normalisation to assist normalise the input data for each layer. For avoiding overfitting, the model incorporates dropout layers with a 0.2 dropout rate.

### 3.3 ConV_BatchNorm_Dropout

ConV_BatchNorm_Dropout or Con2 class combines batch normalisation and dropout regularisation. A number of linear and convolutional layers comprise the architecture. Two convolutional layers with 16 and 32 filters used at the beginning, followed by max pooling, batch normalisation and ReLU activation. 20% of neurons are randomly dropped using dropout rate of 0.2. The cross entropy loss function and Adam optimiser are used to train the model and the weights are saved indicating that it can learn and generalise from picture data.

**3.4 Resnet18**

Torchvision.models module in pytorch is used to create pretrainied CNN known as resnet18 which is an adaptation of ResNet architecture renowned for its capacity to pickup intricate picture data. Pre-trained on ImageNet dataset, it has 18 layers total including 16 residual blocks. A new layer with num_classes replaces the model's final fully connected layer, thus making it possible to adjust the model to a particular categorisation task.

**3.5 Resnet34**

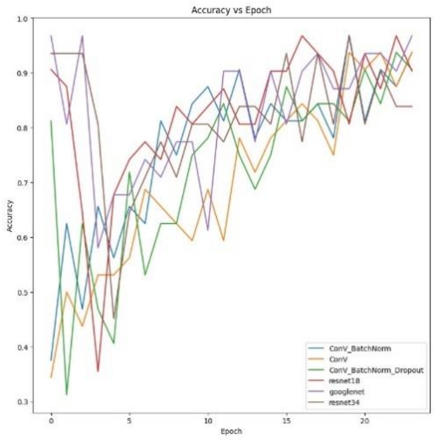
It is a pretrained model called Resnet34 loaded from torchvision.models for image classification which is initalised and adjusted specifically for nine class classification task. The fully connected layer is altered to provide 9 classes instead of the original 1000 classes. Following which it is trained using CorssEntropyLoss and Adam optimiser using 25 training epochs whose performance is assessed on the training set. Post training the model is assessed on batch of photos from dataset, displaying the predicted classes.

**3.6 Googlenet**

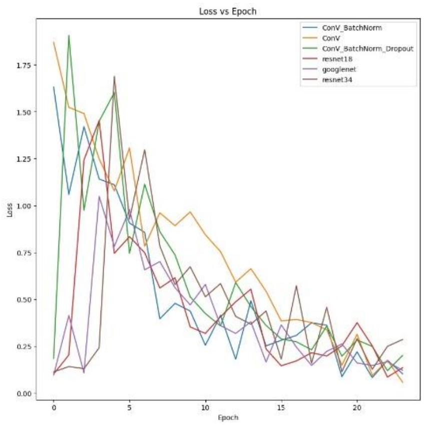
The fully connected layer of Googlenet is modified to produce nine classes with pretrained weights and is replaced with a new layer which generates nine classes when loaded from torchvision.models. Being trained for 25 epochs, the code leverages the knowledge to adapt to particular task at hand using GoogleNet as pretrained model and fine tuning it on dataset naming this method transfer learning.

## 4 Conclusion

The approach evaluates models' performance during training using accuracy and loss metrics thereby saving model weights and optimiser state for further use and the best performing model is selected using these assessment metrics. The metrics are used to assess how well the six models achieve highest accuracy and lowest loss according to the results. The performance is compared using the graphs that show accuracy and loss metrics over a period of 25 epochs. The techniques used in the code namely transfer learning, batch normalisation and dropout regularisation show a deep comprehension of difficulties involved in picture classification problems. The goal to create a reliable and accurate system for classifying medical images has shown how successful deep learning is for image classification tasks by examining CNN designs, transfer learning and regularisation strategies and the main conclusion is to use regulatisation strategies, hyperparameter tuning and cautious model selection to achieve optimal performance. While the project's importance stems its capacity for picture classification jobs, it has a wide range of applications in diverse industries like e-commerce, security and healthcare. The results can be applied to enhance speed of picture categorisation systems to facilitate quicker and more precise decision-making. The project's findings has a big impact on a lot of industries and they can be applied to make picture classification algorithms work better and more accurately. Model Comparison ConV_BatchNorm_Dropout and ConV_BatchNorm perform better than the other models, as shown by the graphs, with ConV_BatchNorm_Dropout obtaining the greatest accuracy and lowest loss. This implies that the model's performance can be effectively enhanced by combining batch normalisation and dropout regularisation.




**Accuracy vs Epoch**




**Loss vs Epoch**

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