A NOVEL APPROACH FOR CLASSIFICATION OFMELANOMA SKIN LESION USING DEEP CONVOLUTIONAL NEURAL NETWORK

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Abstract

Skin cancer is one of the main health issues facing modern civilization. This illness develops when the skin-coloring pigments become cancerous. Dermatologists find it difficult to diagnose skin cancer since numerous skin cancer colours might seem identical. Thus, it is important and helpful to identify lesions early in order to totally treat skin cancer patients. Lesions are what cause skin cancer. Development of automated skin cancer diagnostic systems to support dermatologists has advanced significantly. The use of the vast library of pictures of lesions and benign sores authorized by histology has been made possible by the widespread adoption of instruments backed by artificial intelligence. This study uses the HAM10000 dataset to carry out a comparative examination of six alternative transfer learning networks for multi-class skin cancer classification. To correct the dataset's imbalance, we replicated photos of classes with low frequencies. VGG19, InceptionV3, InceptionResNetV2, ResNet50, Xception, and MobileNet were the transfer learning networks that were used in the study. Replication succeeds at this job with high classification accuracies and F-measures and decreased false negative rates, according to the results. With an accuracy of 90.48, it can be concluded that Xception Net beats the other transfer learning nets utilized in the research. Additionally, it has the greatest F-Measure, recall, and accuracy scores.

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I INTRODUCTION

One of the most prevalent malignancies in the world is skin cancer. The quality of life is significantly impacted. Overexposing skin to UV light from the sun is the most frequent cause. Fair-skinned, sun-sensitive individuals get effects from UV radiation at a greater rate than dark-skinned, less sun-sensitive individuals.

Though it only accounts for roughly 1% of all skin cancer incidences, invasive melanoma is a key factor in skin cancer fatalities. Over the last 30 years, the incidence of melanoma skin cancer has increased significantly. According to projections, there will be 100,350 new cases of melanoma identified in the US in 2021, and 6850 of those instances will result in fatalities.Early identification and prevention of skin cancer are the best ways to manage it. It is important to be aware of any new or changing growths or lesions on the skin, especially those that seem peculiar. A doctor should examine any new lesions or lesions that gradually change in size, shape, or colour. We may now divide skin cancer detection into seven diagnostic groups, including melanocytic nevi, melanoma, benign keratosis-like lesions, basal cell carcinoma, actinic keratosis, vascular lesions, and dermatofibroma. A dermatologist who specializes in the identification of skin cancer often follows a set protocol, first visually inspecting the suspicious lesion with the unaided eye, then having a dermoscopy, and ultimately having a biopsy.

The efficiency of predicting a result grows significantly nowadays when artificial intelligence and deep learning are used in medical diagnostics as opposed to relying just on a visual diagnosis, Along with the medical industry, several other industries have used machine learning. An essential artificial intelligence technique for feature selection and object categorization is the convolutional neural network (CNN). With the use of their dermoscopic pictures, Deep Convolutional Neural Networks (DCNN) categorise all skin lesions discovered during the diagnosis of skin cancer into seven distinct groups. DNNs have an attractive effect on medical image categorization while requiring a lot of data for training. DNNs use high speed GPUs to train a network of large-scale datasets, producing improved results. In processing big datasets, deep learning algorithms supported by these powerful GPUs have shown superior performance to humans in identifying skin cancer.

II LITERATURE SURVEY

The last ten years have seen a rise in interest in deep learning. The categorization of illnesses has made extensive use of convolution neural networks. If the datasets only include a small number of training examples, CNN architecture training is difficult. To handle a new dataset with a variable spatial resolution, a varied number of bands, and variations in the signal-to-noise ratio, a partly transferable CNN was suggested. A novel approach using transfer learning to deal with multi-resolution images from various sensors via CNN is proposed based on experimental results using various state-of-the-art models that show that partial CNN transfer with even-numbered layers provides better mapping accuracy for the target dataset with a limited number of training samples. The learned weights from CNN's training on a common picture data set were applied to additional data sets with various resolutions. Initially, there were just two classifications for skin cancer diseases: benign and malignant. 90% accuracy was attained by Canziani et al. using machine learning methods like K-Means and SVM. In order to accurately predict melanoma, Codella uses the ISIC 2017 dataset, which contains three kinds of skin cancer. However, the dataset's bias and insufficient dermoscopic feature annotations led to erroneous findings. Another attempt at classifying skin lesions using the same dataset and introducing a suggested lesion indexing network (LIN) was successful in achieving the 91.2% area under the curve. It was, however, presented at ISIC 2017, and no new work has been produced for ISIC 2018. Additionally, some statistics categorise skin lesions into 12 separate groups. Han utilised the combined 19,398 photos from the Atlas site, Med-node dataset, and Asan dataset, which were split into 12 categories. He classified data using the Resnet architecture, and his accuracy was 83%. His research also aimed to demonstrate that the suggested dataset was superior to others used for comparison. With the HAM10000 dataset, seven distinct kinds of skin lesions, and MobileNet, Chaturvedi et al. were able to identify skin lesions with an accuracy of 83%. Milton demonstrated transfer learning techniques that employed two epochs of freezing and fine-tuning that were trained on the HAM10000 dataset. PNASNet-5-Large was employed in this case, and it provided an accuracy of 76%. It is more difficult to generalise the characteristics of the lesions since the

HAM10000 dataset is imbalanced and has a considerable variation in the number of total pictures for each class. On the HAM10000 dataset, Nugroho's unique proprietary CNN model obtained 78% accuracy. Kadampur presented an online, non-programming approach for HAM10000 illness categorization and cloud training. Although the aforementioned study works had the benefit of offering a simple algorithm approach and tolerable accuracy, the majority of them did not take into account all forms of legions and utilised relatively outdated information.

The majority of publications classified lesions into the three common categories of basal cell carcinoma, squamous cell carcinoma, and melanoma, it was discovered. The classification dataset was not sufficiently large or recent to identify all varieties of lesions. Three goals were established with all of this in mind.

• To divide the HAM10000 dataset's picture data into the seven main categories of skin cancer.

• To detect all forms of lesions seen in skin cancer by using transfer learning networks for feature selection and classification.

• To carry out a thorough analysis utilising several transfer learning models and to correctly balance the dataset using replication on solely training data. The HAM10000 dataset was used in this study to train the skin cancer classification classifier. The training and validation loss, training and validation accuracy, and individual confusion matrices of all six transfer learning nets were compared. The model that had the best accuracy in recognising all lesions was chosen after a comparative examination of accuracy for all of these learning nets.

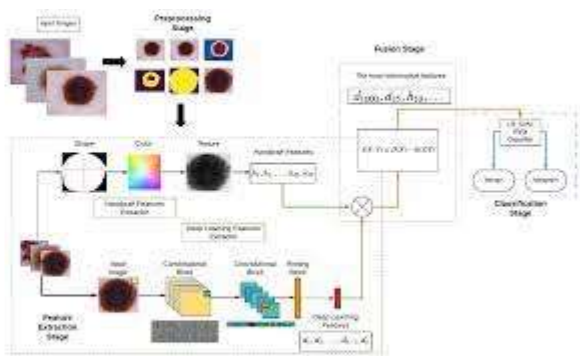
III RELATED WORK

Credible studies have been conducted on image processing, and the field sees daily use in the medical sciences via the application of a variety of machine learning and deep learning methods. Medical professionals are well aware of the benefits of using cutting-edge technology into all aspects of patient care. This paper's methodology owes a great deal to the following studies. Andre Esteva et al. used the GoogleNetInception v3 network to categorise pictures of skin lesions into 23 different types. This method improved accuracy to 72.1%. A total of 129,450 clinical photos representing 2,032 disorders were utilised. The dimensionality reduction technique tSNE was used. The skin lesion categorization system developed by Haseeb Younis et al. made use of MobileNet and a CNN with 93 layers; 5 of these levels were discarded, leaving 88. All layers' weights were frozen and utilised for training, with the exception of the bottom 25. With a 70-30 split between train and test instances in the HAM10000 Dataset, 97.1% accuracy was attained. The ISBI 2016 Challenge dataset for Skin Lesion Analysis 399 was used by V. Pomponiu et al. for the classification of 3 9 RGB pictures with an additional 10000 photos into 2 classes: benign nevi and MM. In order to build a pretrained CNN, the Caffe deep learning library was used. A k closest neighbour classifier (kNN with 10 fold cross validation to evaluate generalisation error and k=2) was trained using features derived from the last three layers of the CNN. The highest possible precision was 93.641.9. Also using this dataset, Adria Romero Lopez et al. applied transfer learning with the pre-trained VGG-16 Network. When the ConvNet network was being fine-tuned, only the uppermost convolutional layers were trained while the bottom ones were held steady. Images were classified as either cancerous or benign using the RMSProp Optimizer algorithm. The system got an 81.33% success rate, a 78.66% sensitivity, and a 79.74% precision. The poorer accuracy of the previously reported research as compared to manual histopathological investigations meant that they were not adopted into practical systems despite their credible findings

IV PROPOSED SYSTEM

In certain forms of skin cancer, such as melanoma and focal cell carcinoma, early identification is critical in preventing the disease from spreading. In any case, the accuracy of the detection is negatively impacted by a number of different elements. Recently, healthcare and medical applications have seen a surge in the usage of image processing and machine vision. In this research, we use CNN to identify and categorise cancer types based on training data from previously collected clinical photos.Our goals for this study include developing a CNN model that can accurately diagnose skin cancer at a rate of >80%, maintaining a false-negative rate in the prediction of less than 10%, achieving a level of precision more than 80%, and performing data visualisation. The suggested strategy is shown to be superior than the other methods examined in simulations.

By comparing several neural network topologies and methods, we want to better understand how they may be used in the diagnosis or categorization of skin cancer. With the HAM10000 dataset, our accuracy was over 80%. We conducted the same experiments using synthetic, enhanced visuals and found results that were quite similar. Accuracy, f-score, Precision, and Recall are the relevant performance metrics here. The best performance in diagnosing skin cancer was found to be achieved utilising the Standard CNN approach.



V METHODOLOGY

Transfer Learning:

Nets Here, we quickly explain the models used in this study and zero in on transfer learning. Machine learning technique known as "transfer learning" involves using a previously trained model in a different setting. It is often used in situations when insufficient training data is available. Data augmentation, however, may address this underlying data deficiency. Melanoma and benign lesions have a lot in common, making it difficult to tell them apart. This is why we require transfer learning. In addition, transfer learning is the preferred method for discriminating between lesions that are otherwise quite similar. The model weights of a transfer learning network are fixed after training on a big dataset, and only the last layers are modified to fit a new dataset. In this article, we compared the VGG19 and InceptionV3 models against the Resnet50, Xception, and MobileNet models. To improve the network layers' ability to identify between seven kinds of lesions, we not only employed the frozen weights but also retrained them using our dataset. Using these six transfer learning networks, we trained models on the skin lesion dataset and then analysed their predictions. We also graphed their confusion matrices, training and validation loss, and validation and training accuracy.

Xception The Xception framework builds on the foundation of the Inception framework. The regular Inception modules are swapped out for depth-separable convolutions. It does not split the input data and instead generates a channel-specific map of spatial correlations. After that, the Xception net executes an 11 depth wise convolution, which is better than Inception V3 on larger datasets and somewhat better on smaller datasets since it captures cross-channel correlation.

Data Augmentation:

We found that many photos in the dataset were duplicates of others, which is bad for the accuracy of our models. We counted up all 5514 distinct photos included in the collection. We divided these pictures into a 20% test set and an 80% training set. The remaining 10% of the data set was used for validation purposes. About 4000 photos were used for training, which is quite low. Furthermore, the courses were imbalanced, with some having significantly more examples than others. Melanocytic nevi had 3179 photos after duplicates were removed, but Dermatofibroma had just 28. We solved this issue by duplicating the group with less data by a factor that would provide numbers that were close to those in the group with more data.

While high accuracy was achieved after training the model with the original training dataset, the true picture could be seen by inspecting the classification matrix. Since Melanocytic Nevi were the most common, they were the ones most often categorised. The model's inability to predict or identify additional low-frequency groups was indicative of its bias. In order to solve this problem, it was necessary to normalise the number of classes and train the model to distinguish between them. To ensure that each category in the dataset included the same amount of photos, their relative frequencies were increased. This means a more robust and healthy model might be achieved.

Pre-processing:

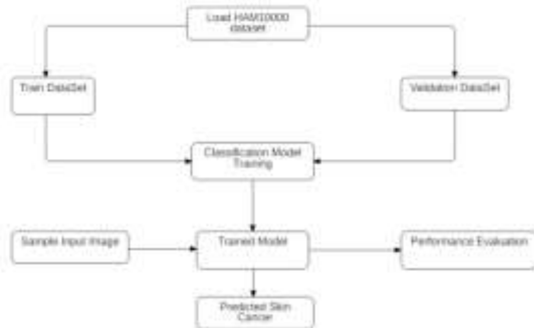
Following the picture acquisition operation, we processed the images. Red, Green, and Blue (RGB) coloured data were divided into three channels. Normal pixel levels range from [0-255]. The photos are normalised as part of the image preparation procedure. The mean and standard deviation of each picture in the dataset are computed during normalisation. The starting photos were subtracted from the mean of all the photographs, and the result was then divided by the standard deviation. The seven disorders, however, were one and hot encoded, meaning that a binary column was made for each category.

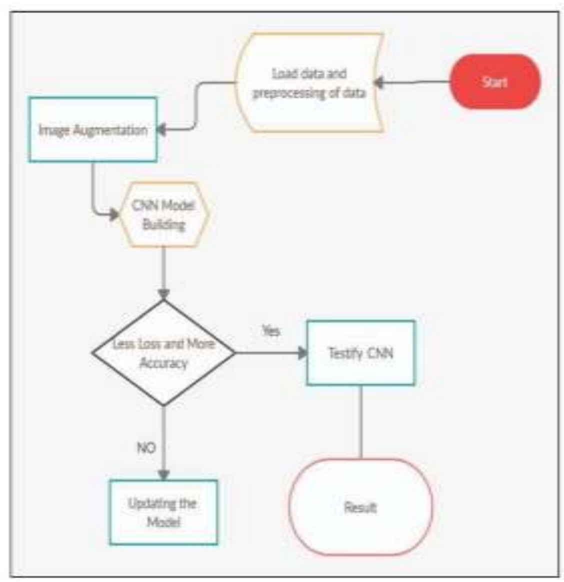
Feature Extraction:

The most important phase of categorization is feature extraction. Pre-trained transfer learning models were used to extract features. This entails identifying key elements in a picture and extrapolating information from them. To create a model, many CNNs are piled on top of one another. Pre-trained models like VGG19, InceptionV3, Resnet50, Xception, InceptionResNetV2, and MobileNet were employed in this case. The Imagenet weights were utilised by each of the aforementioned pre-trained networks. Max Pooling, which determines the maximum value of each feature map patch, Flatten, which reduces a three-dimensional array into a one-dimensional array, Dense layer with 128 neutrons, and finally Dense layer with seven neurons, which represent seven distinct diseases with sigmoidal activation function, made up the bottom layers.

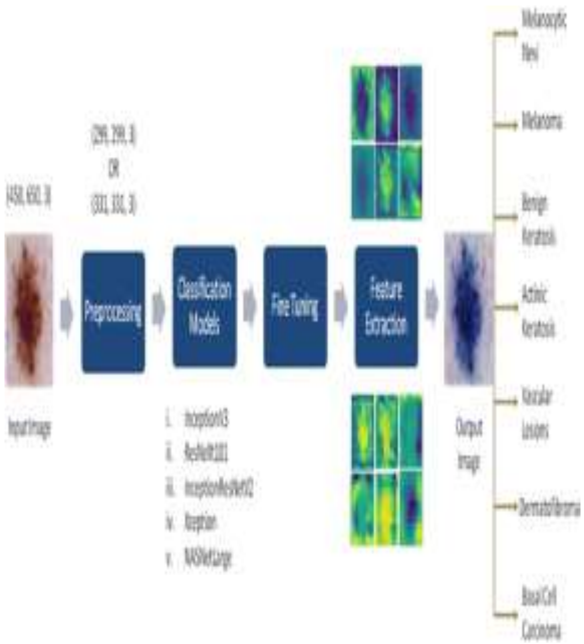
Classification and Evaluation:

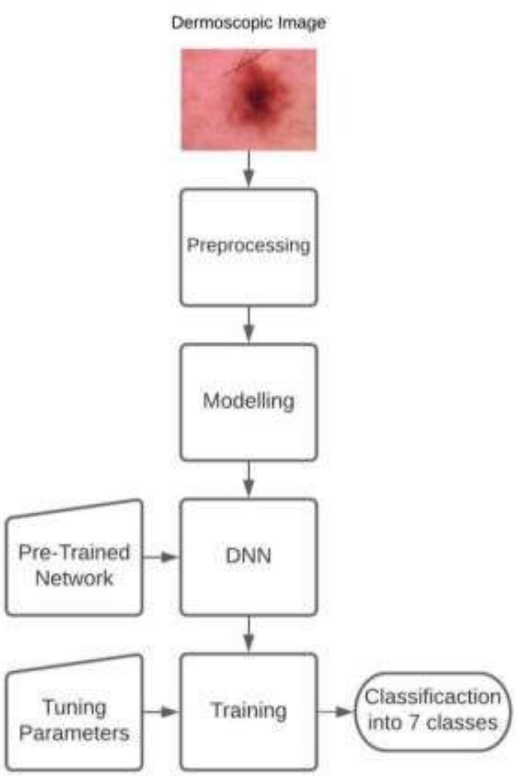
The last layer generates an array of seven values that represents the likelihood of each illness type. Seven distinct types of skin malignancies were represented by the class number. Actinic keratosis (class number 0), basal cell carcinoma (class number 1), benign keratosis-like lesions (class number 2), dermatofibroma (class number 3), melanocytic nevi (class number 4), melanoma (class number 5) and vascular skin lesions (class number 6). During the evaluation phase, we used a validation dataset to validate the various nets for the skin lesion dataset





VI ARCHITECTURE





VII IMPLEMENTATION

Image Acquisition

Image capture is the initial stage in the Dangerous Object Classification process. The dataset for dangerous objects was of a high calibre and was taken from an open Github source.

The complete sample set is split into three sections: testing samples during the testing phase, training samples during the training phase, and validation samples. A positive sample is a picture depicting a patient's behaviour, whereas a negative sample is a background image. The sample set is further separated into positive and negative samples.

Annotated Dataset Collection

A knowledge-based dataset is produced by properly classifying the gathered photos.

Image Processing

The acquired pictures that will undergo pre-processing are further improved throughout processing, especially for image characteristics. The photos are divided into segments during the segmentation process, which is used to remove potentially dangerous objects from a dataset.

Feature-Extraction

The ReLU is used to link the convolutional layers after each iteration, and these layers are responsible for extracting image features from the downsized pictures. The feature extraction size is reduced when the max and average values are pooled. Both the convolutional and pooling layers serve as final filters to provide the desired picture features.

Classification

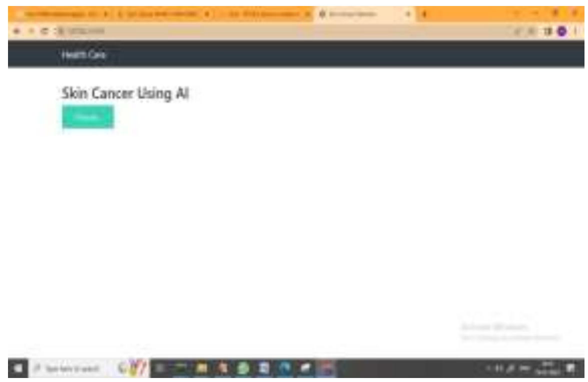
Finally, we perform image classification to teach deep learning models how to recognise and categorise pictures based on learnt visual patterns. The authors employed Python, OpenCV, and the Faster R-CNN model in an open-source implementation made possible by the TensorFlow module.

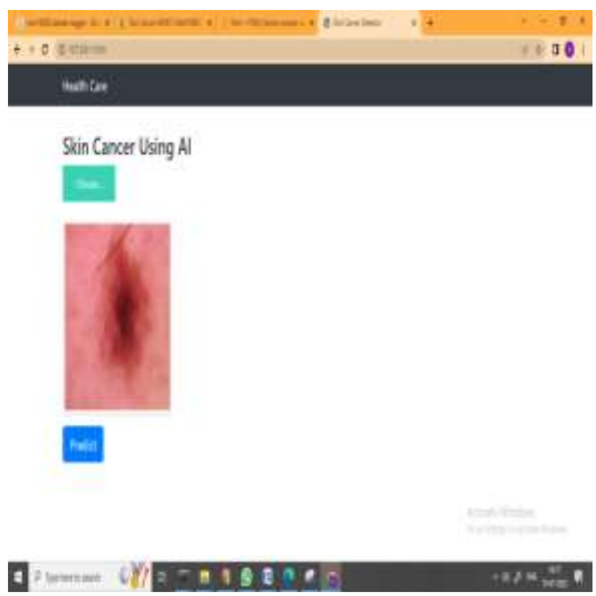
Deployment

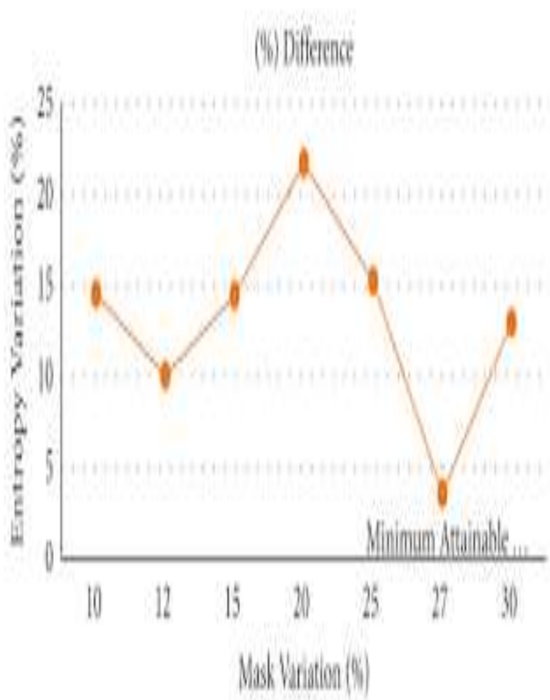
In the last phase of the machine learning life cycle, we put the learned model to use in an operational setting.

We put the above-mentioned model into production if it provides us with a satisfactory outcome within a reasonable amount of time. We will make sure the project is increasing its performance by analysing the data we have before we release it into the wild. The deployment stage is analogous to completing a project's final report.

VIII RESULTS







IX CONCLUSION:

Everyone has lost a lot and gained a lot as a result of the COVID-19 scenario. While many people have become ill with coronavirus and lost their lives, the damage done by this virus pales in comparison to that which would have been done by the imminent penetration of the ozone layer by UV rays. As a result of the epidemic and people remaining inside, the hole in the ozone layer, which had been growing daily, has begun to close. More people's lives can be saved now that skin malignancies can be discovered with these technologies and treated at an earlier stage.

This study demonstrates that a variety of data augmentation and transfer learning techniques may be used to provide competitive classification results. With the help of the data augmentation technique, we were able to collect roughly 32k photos, from which we extracted the necessary features to achieve the desired outcomes. Xception Net is judged to be superior than the other transfer learning nets in use. Label 0 (Akiec) and Label 5 (Mel) were found to be the most wrongly identified due to their striking similarity to innocuous skin patches. Xception Net gives us a precision of 90.48 percent. It has the greatest results for recall

(89.57), accuracy (88.76), and F-Measure (89.02). Results predicted by InceptionResNetV2 and MobileNet are quite similar to those predicted by Xception Net. The most reliably identified skin lesion is melanocytic nevus. As mortality from skin cancer continue to rise, more in-depth study of the topic is urgently needed. The algorithms utilised in this study are not transfer learning techniques, and it is possible that with some fine-tuning, the results may be more accurate.

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