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Hybrid Application Based Skin Lesion Analyzer Using Deep Neural Networks

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Abstract--*Skin cancer with more than 5 million cases reported every year. Early detection can increase the probability of survival. In recent study it was shown neural networks outperform medical board certified doctors in classifying lesions as cancerous. We intend to build a whole system encompassing Image capturing processing it by neural net , sending the response back to the device and formulating a report for the user. We intent to use CNNs to classify the image of skin lesion into 7 categories of cancerous lesions: Melanoma, Benign Keratosis, Actinic Keratoses, Dermatofibroma, Vascular skin lesion and Basal Cell Carcinoma. Our goal is to make the system easily usable by untrained users and make detecting skin cancer easy with higher efficiency.*

Key words--*Neural Networks, Image Processing, Convolu-tional Neural Networks, Skin Cancer Detection, Skin Lesion Imaging, App Development, Localization Algorithms, Cloud Computing, GCP, Compute Engine, App Engine.*

I. INTRODUCTION

Skin Cancer is a major kind of cancer with around 5 million reported cases worldwide every year. The major cause of skin cancer is exposure to UV rays. Diagnosing skin cancer generally included the skin lesion being examined by a doctor. Recent studies have shown neural networks to be more efficient in classifying lesion as cancerous as compared to trained doctors. Misdiagnosing or late detection of cancer can lead to a higher mortality rate and less chance of cure. The goal of this project is making detection and classification of lesions on the skin easier. Not all the marks on skin are a matter of concern but early detection and treatment of cancer can save lives. So this gives the user a way to check if there's a chance of the mark on your skin being cancerous. The aim of this project is to detect and analyse such a correlation using neural networks. It is expected that the outcome of this project will lead to automated classification of skin lesions.

II. LITERATURE SURVEY

The following papers were read and analysed for the refer-ence of this paper. A brief image has been presented here.

1) Andre Esteva et al. 2017," Dermatologist-level classification of skin cancer with deep neural networks." Contribution: Claimed to classify skin lesions at par with board trained dermatologists. Methodology used:

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Convolution Neural Networks for Image Classification. Issues Faced: CNN can classify skin lesion with an accuracy of 75%.

2) Titus J. Brinker et al. , 2019 “Deep neural networks are superior to dermatologists in melanoma image classification.” Contribution: Proved that neural networks can outperform trained doctors when it comes to skin cancer detection Methodology Used: Comparative study Issues Faced: Neural networks accuracy:82%, Doctors:76% This shows neural networks are more accurate than doctors.
3) Samy Bakheet et al. , 2017 “An SVM Framework for Malignant Melanoma Detection.” Contribution: Showed how SVM can be used to diagnose skin cancer Methodology Used: SVM were used with optimized HOG features. Issues Faced: This method can classify with high accuracy into malignant or benign. SVMs cannot be used as it is a traditional technology and becomes algorithmically complex for larger datasets and is prone to overfitting.
4) Andrew G. Howard et al. , 2017 “MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications” Contribution : Gave how mobilenets can be used for mobile vision application to reduce processing time Methodology Used: Mobile nets use depth wise convolution instead of a whole convolution layer. Issues Faced: This network is much faster than normal CNN but has reduced accuracy. Mobilenets compromise on accuracy, we will not be using them as we are aiming for maximum accuracy.
5) Paris Stagkopoulos et al. 2016, “Automated skin lesion assessment using cloud platforms.” Contribution: This contributed to show how cloud technology can be used to carry out extensive processing for neural networks. Methodology used : All processing of the neural network was shifted to the cloud, this helped reduce load from small processors in mobile devices Issues Faced : This can be used to give extensive processing capabilities to existing hardware. We will be utilizing the same cloud platform to run our model as a service.
6) Zijun Zhang et al.2018 “Improved Adam Optimizer for Deep Neural Networks” Contribution: Adam optimizer is a method for optimization which can be used in place of gradient descent. Methodology used: It is better suited for large datasets and especially good for noisy data. Issues Faced: Adam optimizer is computationally efficient and works better on our requirement. Makes training model easier.

III. INFERENCE FROM THE SURVEY

Andre Esteva et al. 2017 , ”Dermatologist-level classifi-cation of skin cancer with deep neural networks.”:Claimed to classify skin lesions at par with board trained dermatol-ogists. Samy Bakheet et al. , 2017 “An SVM Framework for Malignant Melanoma Detection.”: Showed how SVM can be used to diagnose skin cancer. But SVMs need many parameters and don’t perform well when the number of classes increase.(Prone to overfitting). Andrew G. Howard et al. , 2017 “MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications”: Showed mobilenets can be used for mobile vision application to reduce processing time Paris Stagkopoulos et al. 2016 , “Automated skin lesion assessment using cloud platforms.”: This contributed to show how cloud technology can be used to carry out extensive processing for neural networks thus reducing the computational stress on mobile devices. Zijun Zhang et al. 2018 “Improved Adam Optimizer for Deep Neural Networks”: Adam optimizer is computationally efficient and works better on our requirement. Makes training model easier.

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IV. PROPOSED SYSTEM ARCHITECTURE

1. Client - Server Based application. Client will send pictures to the servers. At cloud servers we'll have CNNs who will process the image and classify it.
2. Once the results are generated server will send response to mobile application where One signal Push Notification service will be used to notify user that results have been generated.
3. The CNN is optimized further by using adam optimizer instead of gradient descent.
4. Results will be displayed to user as reports. User can download these reports as pdf for further reference.

V. NOVELTY IN METHODOLOGY

System: According to medical news today, there is currently no accurate system in place that can help untrained people to detect skin cancer. We aim to build a complete system that enables any untrained user to get a pre - diagnosis of a lesion on their skin.

Pre processing: Our system uses SMOTE algorithm to bal-ance the unbalanced classes using object localization (YOLO) to train the model accurately.

We have achieved an accuracy of 89% on the validation data set.

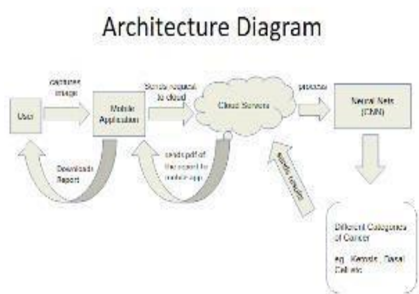

Figure 1: Proposed Architecture

As opposed to 75% for the model without image aug-mentation. Cloud architecture : For such heavy computations, mobile devices can't be used so we have deployed our model in GCP Cloud platform to ensure the app works efficiently.

VI. MODULES

There are a total of five modules in this system.

1) User Module: Defines GUI of the application Takes Image as input from user in Mobile Application. Takes in other parameters such as symptoms , any illness etc from user. Sends the inputs to clouds for further processing. Displays results to the user.
2) Convolution Neural Networks: Trains the dataset. Process the incoming image and information through various parameters. Determines probability of type of cancer. Sends Results in terms of probability.

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3) Cloud AI Platform: Sets up Neural Nets on the cloud server. Train Neural Nets on Cloud Server for better results. Deploy Neural Nets on Cloud Server. Provides with Bucket to upload neural nets. Helps in fast processing training of model.
4) Server Module: Contains app scripts. Contains database. Acts as a link between user and CNN. Generates final results as a report, sends it to user and stores it in a database. Responsible for overall performance of system.
5) Database: Stores User details. Contributes in sending notification alerts to the segmented users. Helps in improving accuracy of CNN. Helps in storing and keeping proper track of results.

VII. MOBILE APPLICATION WORKFLOW

1) User clicks the picture. The application crops the picture, localizing on the said lesion and sends an http request to the server.
2) The NodeJS api sends the image to the deployed model on the server.
3) The image is fed into the model. The Convolution Layer scans the image through a pixel window. Now the Pooling layer removes any noise from the image. The ReLu layer introduces linearity using the Relu Function. ReLu(x) = max(0,x)
4) The final layer uses a softmax function to give proba-bilistic values for each of the seven classes.
5) The final result is sent back to the device as an http resonse.
6) A pdf file is generated with a detailed report and further suggestions to if the said lesion is dangerous and further steps.
7) A push notification is sent to the user's device that the report is ready to be downloaded.

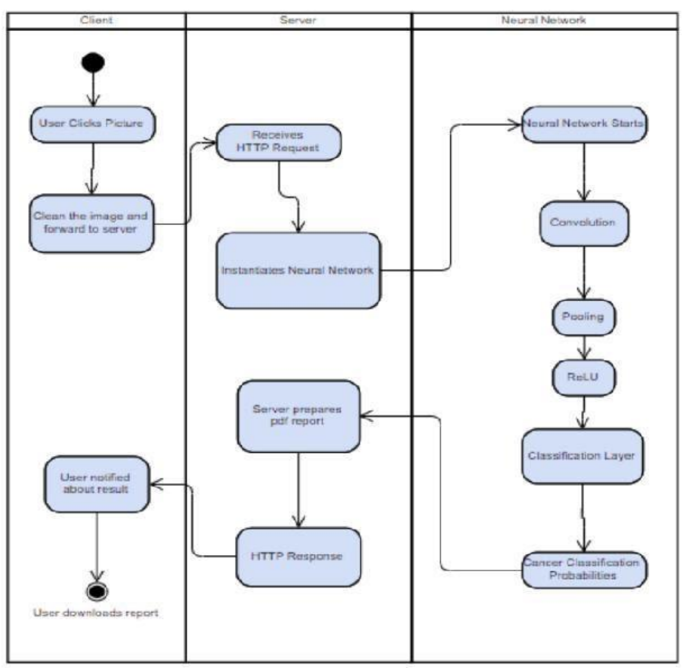

Figure 2: Use Case Diagram

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VIII. ALGORITHMS USED

Image Augmentation – Since the images for the training dataset are quite less and CNN requires a large dataset we use image augmentation to rotate and mirror the existing images. SMOTE – SMOTE(Synthetic Minority Oversampling Tech-nique) is an oversampling technique used to restore balance if unbalanced classes are present in the data. It uses KNN to generate similar data points so that the final model is not biased or overfits those classes which have a high number of data nodes.

YOLO – You Only Look Once is a real time object detection and localization algorithm, we use it to specifically train our model on the skin lesion and not the entire image.

CNN – Convolution, Pooling, ReLU Layers for Image pro-cessing.
Adam Optimizer – Minimization function ; more efficient alternative for gradient descent.

IX. IMPLEMENTATION SOFTWARE

1) Convolution Neural Networks.
2) Ionic Framework : Hybrid Application Development framework allows our app to be compatible on all platforms.
3) Google Cloud Platform to run CNN model.
4) Nodejs as server side scripting language.
5) One signal Push Notifications.
6) MongoDb Databases.

X. RESULTS AND MODEL PERFORMANCE STATISTICS

After training for 30 epochs, our model was able to achieve an accuracy of 89%. We can see from the figure(accuracy vs epochs) the accuracy curve tends to flatten out around 12 epochs. The validation accuracy is a bit higher than the training accuracy. This means that our model was able to achieve a better accuracy in the images not processed before which implies it would work well with real life examples as well.

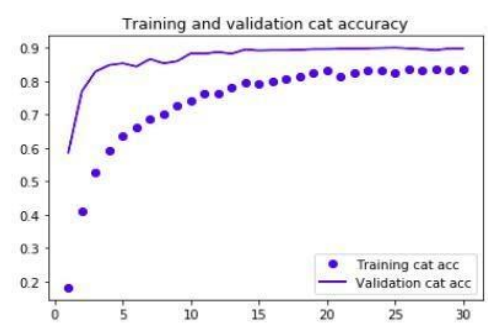

Figure 3: Accuracy vs Epochs

From the Loss vs Epochs graph it can clearly be seen that training and validation loss tend to converge towards the end. This means our model is neither over fitting nor under fitting. Our model is balancing the bias and variance quite well. The lines tend to converge near the 16 epoch mark. This suggests that 16 epochs were enough to train the model.

Thus, our model tends to work well with real world exam-ples and is not biased towards any class as class balancing was successful. Given enough samples to train from, this model shows promise and can be implemented on a larger scale.

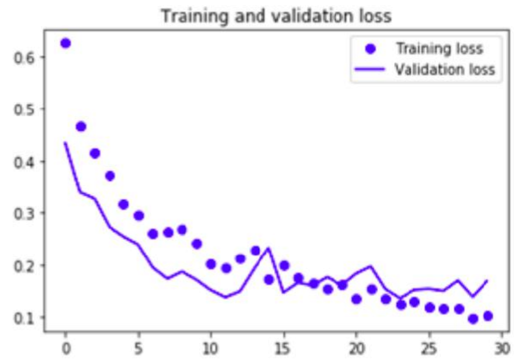

Figure 4: Loss vs Epochs

XI. CONCLUSION

The proposed system is expected to work as an entire system for diagnosing skin cancer at an early stage.The system implements CNN which will be able to predict the type of cancer with an accuracy of 85% . Leveraging the high computing power of cloud , Neural networks were able to show results even on low performing mobile devices. Thus , using this system user is able to perform a pre - diagnosis which helps in catching skin cancer at an early stage.

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