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## Melanoma Classification using Convolutional Neural Network Model Integrated with Tabular Model

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### ABSTRACT

*Melanoma is a major skin cancer type that has a very high death rate. The various sorts of skin abrasions cause an imprecise analysis because of their high resemblance. Precise categorization of the skin abrasions in the premature phase will allow dermatologists to cure the affected individuals in well time and hence saving their lives. This is backed by a research that shows that 90% of the cases are curable, if identified in the initial phase. With the advancements in the computing power and image classification, automatic detection of the melanoma using computer algorithms has become far reliable. With many methods used, neural networks prove to be the best solution devised to attain the highest accuracy in classifying melanoma through early symptoms. We did our survey to find the drawbacks of recent models that serve this purpose with the goal to overcome them and provide a better solution. With the findings based on this survey, we proposed a model that strives to overcome the drawbacks concluded from the previous models. With an accuracy of ~96%, the proposed model provides better solution in predicting whether the skin lesions are malignant or not.*

**Keywords:** Melanoma, Neural Networks, Lesions, Automatic Detection

### 1. INTRODUCTION

In the year 2018, the World Health Organization stated that approximately there were 1.4 crore new cancer patients and nearly 96 lakh deaths round the world due to cancer. These figures shows that cancer is the top contributor to deaths. To begin with, skin cancer develops on the epidermis, which is the top layer of the skin visible to unaided eyes. Skin cancer is one of the most foremost cause to the global deaths. There have been various kinds of skin cancers found. Melanoma's a familiar form of skin cancer that is typically the most cancerous lesion when equated with types of other skin lesions. It is also one of the rapidly spreading cancer of skin, which in recent research observations shows that the number of infected individuals with skin cancer are growing each year. To save human lives, automated computer-aided are taken in use for the quick and accurate results of these skin causing cancer. Computer-Aided

Diagnosis (CAD) systems are one such method that has been in use for multiple disease identification at early stages. To provide dermatologists with an accurate diagnosis, image relied CAD methods use photographs of skin lesions shorn of any other medical details. In addition, various skin lesions may be identified by an image-based CAD method based on features derived from the colours in dermal photographs. Built on its precision, a CAD method could help in premature diagnosis of skin cancer and create opportunities to save human lives beforehand.

Dermoscopy, furthestmost known skin imaging procedure, has shown an increase in melanoma detection relatively compared to that of the bare eye. With researchers finding ways to classify these images they began with using colour texture features and wavelength network features to classify the lesion based on its colour. This included methods such as wavelength network, color text features, neural networks, deep learning and many more. Through these methods of automatic detection, we faced some crucial problems. Firstly, in the very beginning, classifying the skin lesion was a tedious task as their shape, size and color, texture and other details were similar. Secondly, with multiple similarities between melanoma and non-melanoma lesions, concluding which lesions were cancerous was not easy. Moreover with distortions like hair, veins and other marks in the limited available datasets increased the difficulties to train the models as clear datasets were inadequate in number. Lastly, the different races, genders and location to which individuals belonged led to lesser accuracy while testing the models. Several methods were used to overcome these challenges. Initial attempts like the one by Amir Reza Sadri used 3D multidirectional (colour texture feature) CTF matrix to evaluate the images and then scaling them using a greyscale spatial dependence matrix to find the intensity of the melanoma cells. M. Q. Khan, with his team of researchers in their paper, uses geometrical, colour and textural features all together with image segmentation to create a model that used K-means clustering on the images. This method is a known versatile technique that works well with large datasets as well. A. Sáez and teams' research of 2016 is based on the thickness of the melanoma lesions. It is known that including thickness as a factor can increase the model accuracies up to thirty-five per cent. The thickness can be divided into three stages, ranging from 0.76mm to 1.5mm. But these parameters stand-alone cannot achieve high accuracy.

These approaches succeeded in achieving accuracy in the training and testing databases. However, as the dataset was small and didn't consist of clean data, the model could not provide high accuracy result in images that had hair or veins or images without proper lightning. This led to pointing out problems in the methods and its effectiveness.

With developments in machine learning algorithms and methods and better neural networks and computing power, scientist started using this approach to work on the latest available data. Zhen Yu and Xudong Jiang used Convolution Neural Networks novel Fisher vector encoding technique to encode the images fed into a Support Vector Machine. This way, the machine is fed with more defining factors because of the FV encoding. Through these methods, they overcame the need for a large dataset to train CNN and produce higher accuracy with smaller datasets as they extracted more features. Developing state of the art algorithms and combining pre-developed algorithms helped improve the models. The obstructions in images like hair, vein and lightning were efficiently removed, giving better outputs. However, Convolution Neural Network requires a massive number of images to be trained. The problem with using image data alone is that the amount of images available in these batches is small.

**2. PROPOSED WORK**

Analyzing the methods used by researchers to overcome the fundamental problems of melanoma classification, this paper takes a unique approach of combining the image data corresponding to the tabular data, which includes the age, gender, race and location of the lesion on the patient and using it as a parameter to train the model. This approach would increase the parameters determining the outcome, thus overcoming two of the crucial problems faced – firstly, lack of parameters and data to train neural networks and secondly, to overcome the global deployment of the model on patients from different regions, race and gender by specifying their details as tabled data. The model is developed using the 'FastAI' and 'image\_tabular' libraries, which sit on top of PyTorch, an open-source Machine Learning Framework. Additionally, we use 'Transfer Learning' and employ 'DenseNet 201' architecture for the task.

FastAI is a deep learning library that offers advanced modules which can rapidly and effortlessly deliver modern results in standard deep learning areas that can be mixed and matched to build new methods. It aims to accomplish both without sacrificing usability, flexibility, or performance. By combining the dynamism of the fundamental Python language with the versatility of the PyTorch library, these concepts can be presented clearly and precisely. It is a versatile and easy-to-use python library that enables its users to create deep learning models efficiently. As it's written on the PyTorch framework, it is also flexible in terms of customizations. The inbuilt functions provided by its developers are concise, which makes the model development seamless, even for amateurs.

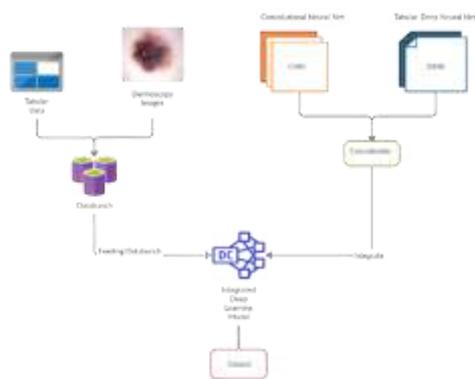


Fig. 1: Proposed Model

The 'image\_tabular' library is a custom library written in PyTorch and made compatible with FastAI functions to enable data and model integration. The users can combine a separate CNN with a Tabular model into a single integrated model for simultaneous training. Similarly, it also fits the image and tabular data into a single variable, which can be passed into the integrated model as data.

Transfer learning's a method of machine learning, where a system is used for an additional task correlated to what it has been already trained for in the initial training cycle. Transfer Learning has revolutionized deep learning. It involves combining a group of custom layers with a pre-trained model for other classification tasks with additional training. It is an advantageous technique as the model already identifies some image features. This reduces training time and effort immensely. It simplifies and provides a solution to the obstacle faced by the inadequate amounts of existing skin lesions datasets; these datasets are not appropriate to train a deep complex model from initial due to the reduced quantity of images. Transfer learning is the preeminent resolution to overcome such difficult. Transfer learning is attained in three stages. First, picking the pre-trained system; the DenseNet is qualified. In the next step, some layers concluding the end of the DenseNet are substituted and are finely-tuned to get the best outcome. The final step includes reusing and adjust the model layers for new (main) tasks. FastAI only supports a few transfer learning architectures, and for our work, we have chosen the Densenet 201 architecture. Densenets require lesser constraints than traditional CNNs; therefore, it does not learn repeated feature maps. Also, they are immune to the gradient problem as each layer has direct access to the gradients from the loss function and the original input image.

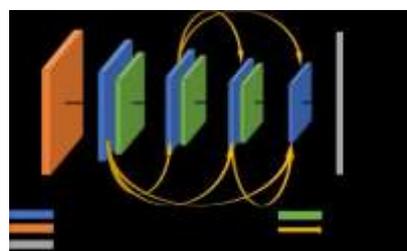


Fig. 2: Densenet 201 Block Diagram

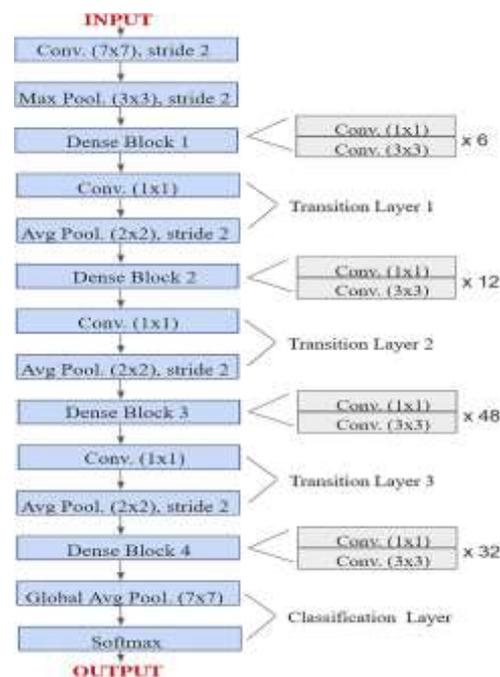


Table 1: Densenet201 Architecture

I. Equations

The equations used in this model to balance the data and to measure it's accuracy are as follows:

$$\text{Weight of Benign Class} = \frac{1}{\left(1 - \frac{\sum T}{n}\right)} \quad (1)$$

$$\text{Weight of Malignant Class} = \frac{1}{\left(\frac{\sum T}{n}\right)} \quad (2)$$

T : Target Variable  
n : Number of rows

3. DATASET

The popular dataset is of the SIIM-ISIC 2019 challenge is used to test and appraise the planned model. This data set included over 33,000 images, of which 32,600 images were unique. This dataset comprises of pictures of HAM10000 in addition to the BCN\_20000 which includes 10000 pictures with dimensions 600 x 450. This dataset was the older challenge of ISIC 2018. While the BCN\_20000 holds ~19425 images of 1024 x 1024 size. The test batch consist of added indefinite lesion that was not existing in the training dataset. DenseNet, aimed for the automatic identification of skin lesions usin transfer learning (knowledge). Experimental outcomes are presented, as discussed in the following subsection. The data set had some poor quality images that hindered the training, making the model less accurate.

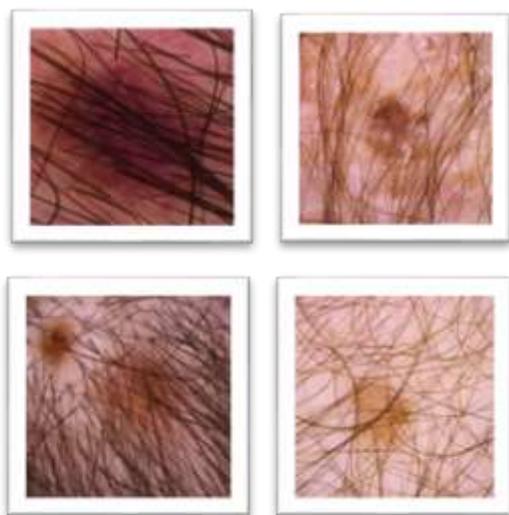


Fig.2: Hairy images in the dataset that might confuse the model

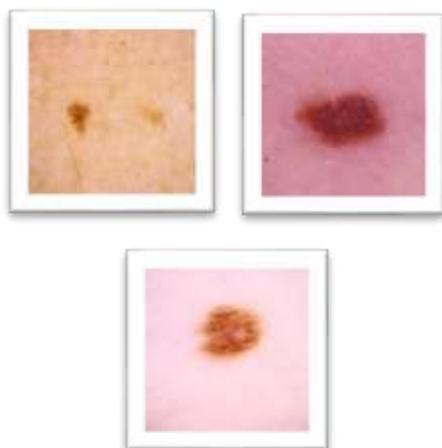


Fig. 3:Some examples of Lesions

4. IMPLEMENTATION

The workflow pipeline has been divided into four modules:

a) DATA PREPROCESSING

By analyzing the image dataset manually, it was found that it contains duplicate images. Having redundancy in the dataset increases the chances of overfitting and might confuse the model as well. Thus, we remove duplicate images and their corresponding records in the CSV file for better model training. The CSV file is also preprocessed using the inbuilt FastAI functions.

b) DATA INTEGRATION

To train an integrated model, we need to integrate the data first. This is done by combining the image data and tabular data in a single 'DataBunch' variable with custom-made functions in the 'image\_tabular' library. This integrated data is also split into training, testing and validation data.

c) MODEL DEVELOPMENT

First, the CNN model is defined by taking Densenet201 architecture as the pre-trained model without the weights. Secondly, the tabular model is defined with optimal parameters such as embedding size, output sizes, layers and dropout. Finally, using the custom 'CNNTabularModel' function from the 'image\_tabular' library, we obtain an integrated model by passing CNN model and Tabular model variables.

d) Training and Testing

The dataset is highly imbalanced, i.e. approximately 98% per cent of the images are of benign lesions, and only 2% are malignant. This is a huge hurdle, as image classification tasks perform well mostly on equally balanced datasets. To tackle this, we pass custom weights to the loss function according to the class imbalance.

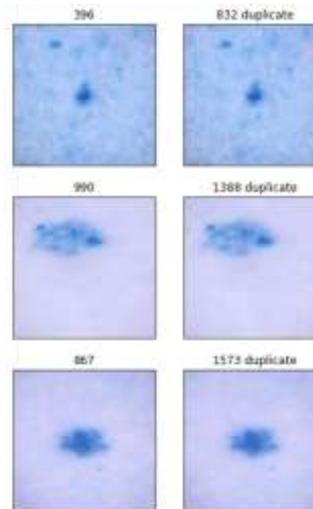


Fig. 4: Examples of some duplicate images in the dataset

We then create the learner variable and pass the integrated model, integrated data, metrics and the loss function as the arguments. The learner variable is split into three layer groups. The first two groups contain the initial layers of the Densenet201, and the last group contains the final fully-connected layers for the concatenated data. We do this so that we can apply differential learning rates provided by FastAI. This method enhances the model training by training particular groups with different learning rates.

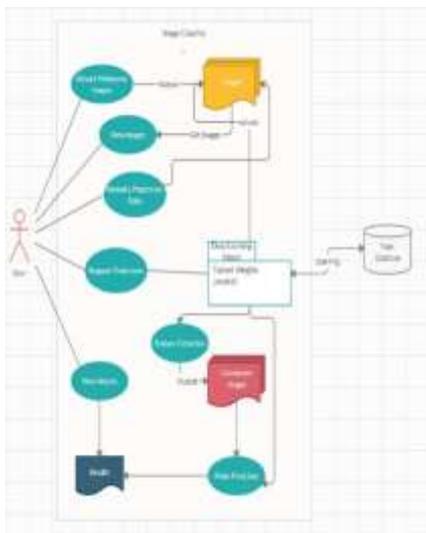


Fig. 5: Use Case Diagram

### 5. RESULTS DISCUSSION

The presented system was trained using Google Colab with a GPU of Nvidia Tesla K80. The initial experiments gave an accuracy of 88%, with ROCAUC 87%. However, repeated experiments to find the optimal learning rate eventually led the model to achieve an accuracy of 95.8% and ROCAUC of 91.6%.

The model was trained two times:

- 1) Training of fully connected layer group by freezing the model. (Epochs : 13, Lr: 3e-6). This helped in generating weights in the new layers inserted by the user.
- 2) Training of the model as a whole by unfreezing the model. (Epochs : 12, Lr : 1.5e-5, 3e-4). Here, the model is trained from scratch. This makes sure the whole model is trained on the dataset for better feature extraction.

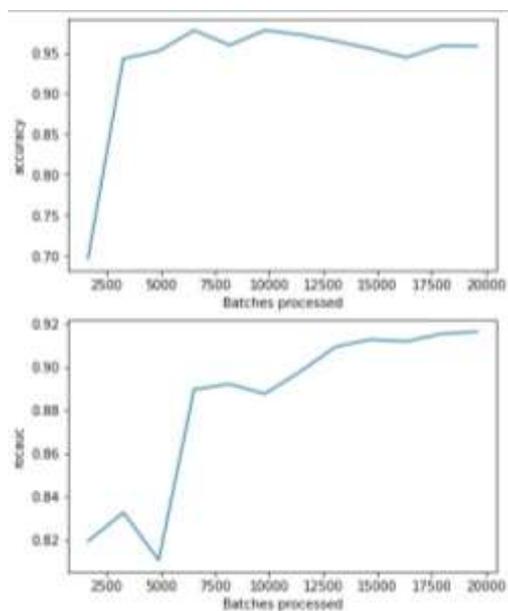


Fig. 6: Final training metrics achieved

The dataset was divided into 80%, 10% and 10%, with 80% for training, 10% for testing and 10% for validation. Each batch sized trained 32 images at once, which were the highest limitations of the GPU used. The training could be better if larger batch size training could be done.

### 6. CONCLUSION

A technique for a challenging dataset has been developed here by means of transfer learning and DenseNet. The proposed can classify malignant and benign melanoma cells with an accuracy of 96%. The performance of the proposed method amplified when the learning layers are finely tuned with the right weights. It also helped to overcome the lack of parameters by combining the tabular as well as image dataset to work on a vast type of images in the real world. The model's accuracy could be increased using a more balanced dataset for training and better images of improved quality.

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