CLASSIFICATION MODEL OF BRAIN TUMOR IMAGES TO CLASSIFY BETWEEN VARIOUS TYPES OF TUMORS

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ABSTRACT

There are various kinds of brain tumors. This study uses three types of samples: meningioma, glioma, and pituitary tumor. Identifying the type of tumor is critical since it influences the kind of treatment. Brain MRI images play a significant role in identification. The manual examination can be a time-consuming operation at times. We hypothesize that transfer learning models can produce relevant results for classifying various types of brain tumors. To demonstrate this assumption, we display the effects of different transfer learning models and compare them to those constructed from scratch. Our research includes data pre-processing and deep learning model training using the MONAI framework as well. We are also using the grad Cam for visual depiction of outcomes.

Index Terms— Brain Tumor, Transfer learning, Xception, InceptionV3, MONAI, GradCam

1. INTRODUCTION

A brain tumor is a clump of aberrant cells growing uncontrollably. [1] Tumor types are determined by the cells from which they originated and the rate at which they grow. Meningiomas are tumors forming in the tissue layer that protect the brain and spinal cord. Because these are slow-growing tumors, they are not threatening. Gliomas develop from the cell that supports and nourishes the neurons. They grow more quickly than meningiomas. Several types of gliomas are challenging to treat. They are the most frequent type of astrocyte (brain or spinal cord tumor), accounting for 30% of all brain and central nervous system cancers and 80% of all malignant tumors [2]. A pituitary tumor is a benign growth or lumps those forms within the pituitary gland. The type, size, and location of the tumor all influence treatment [13].

Identification is critical in determining the severity of the malignancy. A neurological exam, brain imaging, and a biopsy can all be used to diagnose a brain tumor. The evaluation of several neurological functions, such as balance, hearing, vision, and reflexes, can help to determine the varied symptoms. Automatic and quick findings can help to avoid undesirable consequences.

We propose combining the abovementioned models with transfer learning to avoid manual labour and save time. Many studies have been conducted to detect brain tumors using deep learning models [1]. Our research focuses on transfer learning models such as Xception and IncepptionV3, MobileNet, and the MONAI (Medical Open Network for AI) framework.

2. RELATED WORKS

If a brain tumor is not treated early, it might be fatal. As a result, brain tumor detection is a critical area for researchers.

- One study proposed image segmentation of brain MRI images with HSOM to identify the images row by row [4]. The hierarchical self-organizing map (HSOM) expands the ordinary self-organizing map [4].

- Another study analyzes different CNNs and machine learning algorithms for detecting three different types of brain tumors and indicates that the 2D CNN Auto encoder achieves the highest accuracy.[3]

- Additional brain tumor research on MRI images eemploysmultiple ResNet configurations.[2] They used ResNet(2+1)D, ResNet3D, and ResNet in combination with Convolution.

- Image segmentation of Brain MRI images is performed by a single network based on the dynUNet [5]. It improves cutting-edge fetal brain segmentation methods.

- One article used a deep convolutional neural network to differentiate low-level glioma from high-level glioma.[6] It presents two successful methods for classification that do not involve a manual definition of the region responsible for glioma detection.

3. MATERIALS AND METHODS

3.1 Database Description:

The image dataset covers three forms of brain tumor images: 1) meningioma, 2) glioma, and 3) pituitary. The initial dataset was in the form of a .mat file, which was then transformed into .png files for further processing. The data set was retrieved from Kaggle.

It includes 708 meningioma images, 1426 glioma images, and 930 pituitary tumor images. These brain MRI images are taken from different angles, allowing our convolution neural network model to be generalized on the other real-world dataset.

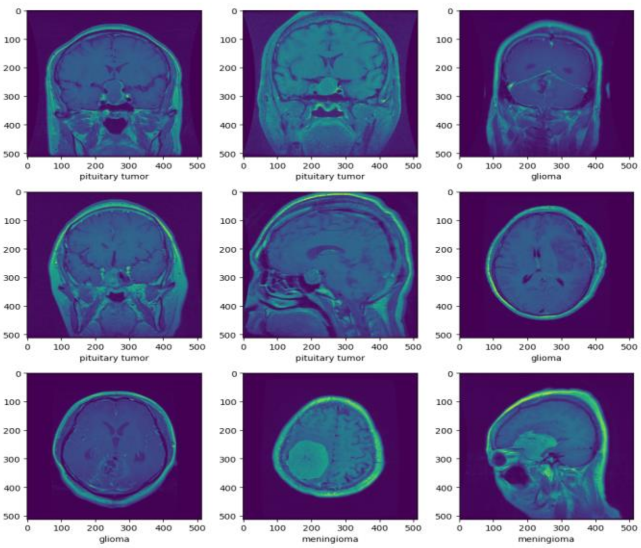

Figure 1 Sample Dataset

The sample dataset is presented above. We use 80% of the data for development and 20% for testing. We use 85% of the development data for testing and 15% for validation.

3.2 Data Preprocessing

Data preprocessing can assist in reducing noise from raw data. It helps in the cleaning and normalization of data. The quality and number of features are critical since they directly affect model learning and accuracy.

Our study uses preprocessed brain MRI images before passing those as input in specific transfer learning models. These pre-processing functions will normalize and re-scale the image’s pixel values from [0, 255] to [-1, 1]. Also, it prepares the input image data in a way consistent with how the transfer-learning model was pre-trained on the ImageNet dataset. This helps ensure that the model performs well when predicting new images.[10]

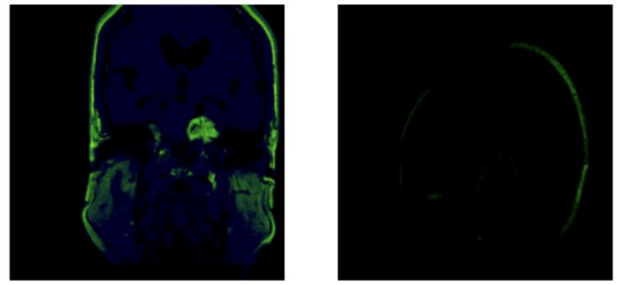

Figure 2 Data Preprocessing (Xception)

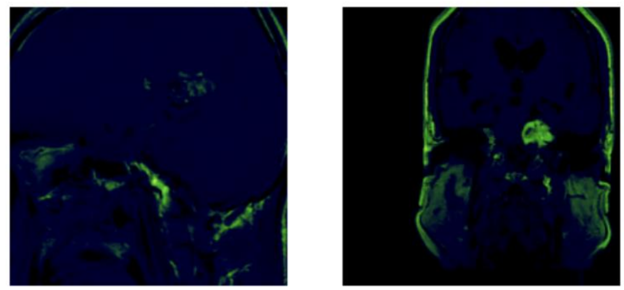

Figure 3 Data Preprocessing (InceptionV3)

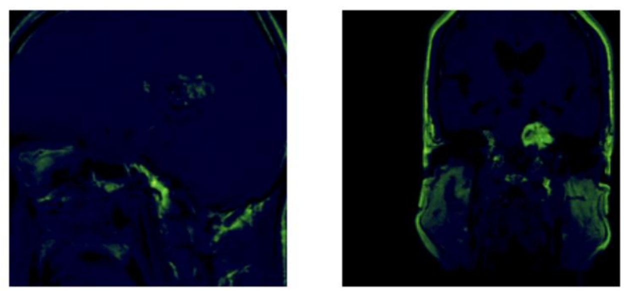

Figure 4 Data Preprocessing (MobileNet)

3.3 Data Augmentation

The primary purpose of data augmentation is to increase the size and diversity of the dataset to build a more robust and adaptable model that can perform well on new and unseen data. In image classification tasks, data augmentation involves applying a range of image transformations, such as flipping, rotation, and zooming. These transformations help to simulate real-world data variations, such as changes in the object's orientation, scale, and lighting conditions, which can enhance the model's ability to recognize objects in diverse scenarios.

Data augmentation techniques provide a way to help machine learning models learn more effectively from the training data and improve their performance on novel data. This can be especially useful where generating additional data can significantly impact the model's accuracy.

For data augmentation, we are using ImageDataGenerator from Keras. To generate the new data, we use many factors such as rotation, height shift, brightness, zoom range, etc.

These are some examples of augmented data derived from the original data.

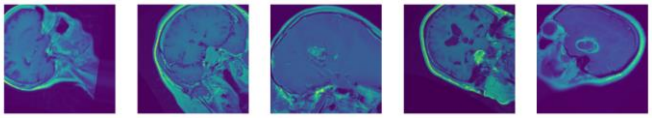

Figure 5 Augmented Data

3.4 Grad Cam

The Grad-Cam highlights the area of the object that plays an essential role in classifying the images. It also helps in determining the patterns that contribute to the feature extraction. Below is the Grad-Cam for CNN models that we have developed from scratch. From the Grad-Cam, it is evident that it highlights the top-left area of the brain that represents the tumor. However, the model is learning some noise which is assumed to be facial tissues on the side surface of the image and the outer skull part.

This observation helped us consider the preprocessing before feeding it to the model as it eliminates the noise or the unimportant part of feature learning. We have implemented the preprocessing in the transfer learning models and the densenet121 model from MONAI.

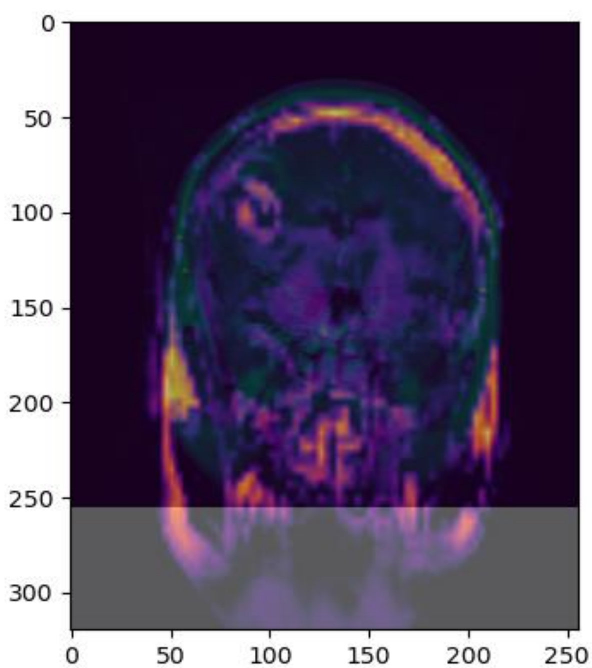

Figure 6 Heatmap using Grad Cam

3.5 Convolutional Neural Network

The CNN uses the Convolution layers and a small filter or kernel over the input data. This will result in feature map generation and pattern recognition.

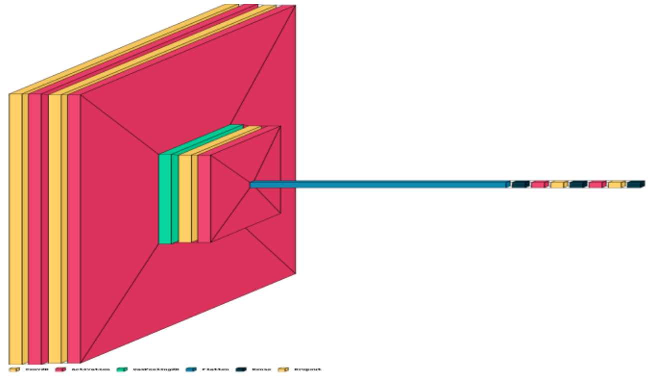

Figure 7 Architecture of CNN

We have used various convolutional, max pooling and dense layers to generate the model from the ground up, which aims to classify different types of brain tumors based on the MRI images. We have received the 13 million parameters as trainable parameters. Here, we have the same number of the trainable and total number of parameters as we are training it from scratch. The dimension with the 256x256 image has been fed to the model, and a 3x3 filter has been applied.

3.6 Transfer Learning

Transfer learning facilitates practical model training when there are few labelled data available. Here, the dataset contains about 2400 images approximately. Well-known transfer learning models can be used to determine the results with less computational capacity. To identify the type of brain tumor, we are using InceptionV3, Xception, and MobileNet in this case. To implement these models, we only kept the base models. We removed their top classifier part, and to finetune it on our dataset, we have built our classifier part, which has batch normalization, dense and dropout layers. Our final layer has three neurons with SoftMax function, each indicating a type of brain tumor.

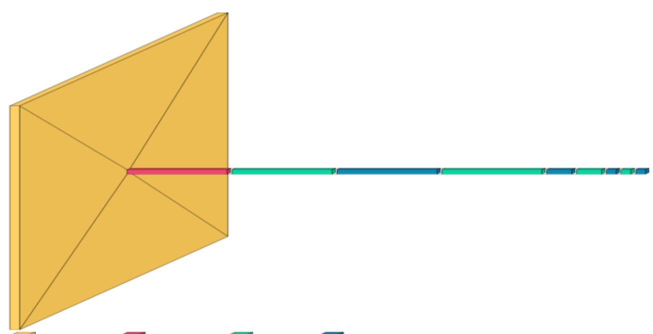

Figure 8 Architecture of InceptionV3 transfer learning model

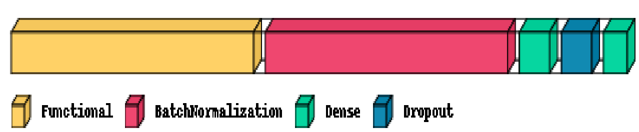

Figure 9 Architecture of Inception transfer learning model

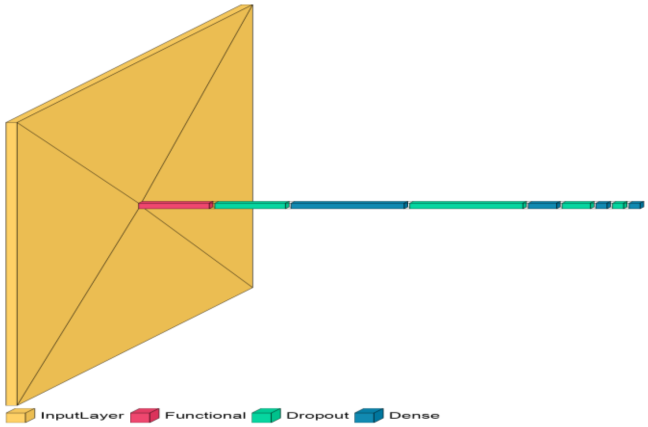

Figure 8 Architecture of MobileNet transfer learning.

3.7 MONAI

MONAI (Medical Open Network for AI) is an open-source system that processes medical images. As our problem set comprises medical images, the MONAI deep learning framework was employed for experimentation. MONAI is designed with a diverse group of pre-processing, post-processing, and evaluation functions tailored explicitly to medical images. It offers a user-friendly and straightforward approach to loading and processing medical image data. Furthermore, MONAI supports distributed training, enabling users to train their models on multiple GPUs or a cluster of machines. However, due to technical constraints within the Kaggle environment, we were unable to leverage the GPU capabilities of the MONAI framework for training our models. [12]

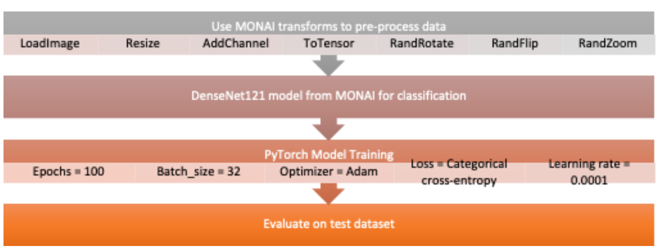

Figure 9 Experiment setup for MONAI

We use predefined functions such as LoadImage, AddChannel, RandFlip etc., for the preprocessing. We are using DenseNet121 pre-trained model from the MONAI library. [11] which contains 121 layers with trainable weights with the standard ResNet structure. We are training the model with the Adam optimizer, categorical cross entropy as a loss function with a learning rate of 0.001.

4. RESULTS AND DISCUSSION

We have trained and tested various models and recorded the results to achieve the optimum accuracy for brain tumour classification. The CNN model that we have developed has the lowest accuracy. Transfer learning models have good accuracy. In which Xception has the best accuracy.
However, InceptionV3 has approx. 23 million, and Xception has approx. 22 million trainable parameters. While MobileNet contains approx. 4.2 million trainable parameters, which makes it more computationally suitable to train.

Sr no	Model	Accuracy
1	CNN	77.81%
2	Xception	96.41%
3	InceptionV3	94.78%
4	MobileNet	84.34%
5	DenseNet121	92.17%

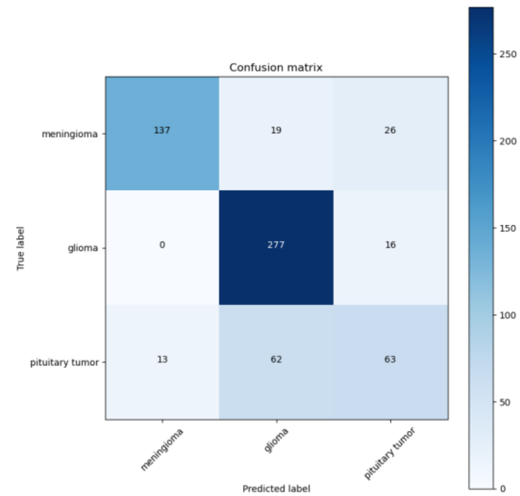

Figure 10 Confusion Matrix for our CNN from scratch

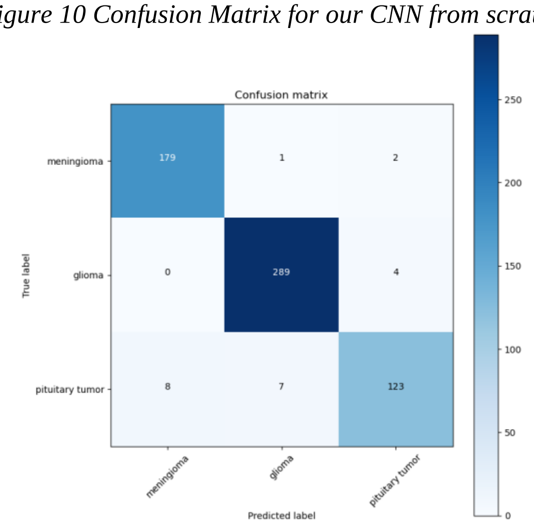

Figure 11 Confusion Matrix for Xception transfer learning

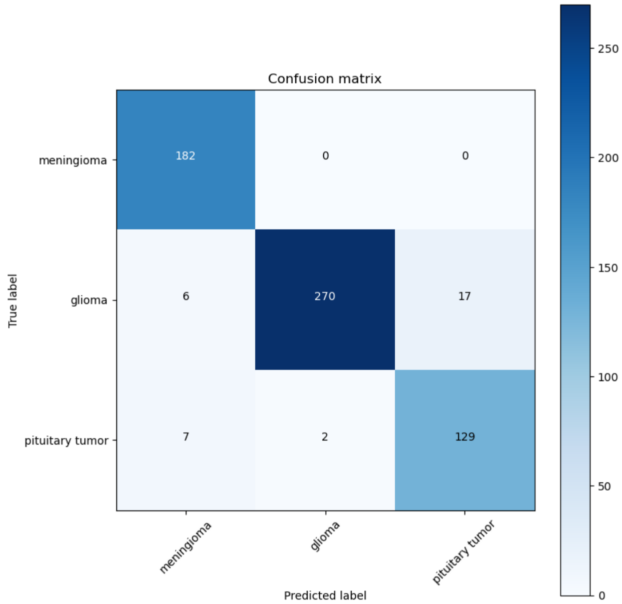

Figure 12 Confusion Matrix for InceptionV3

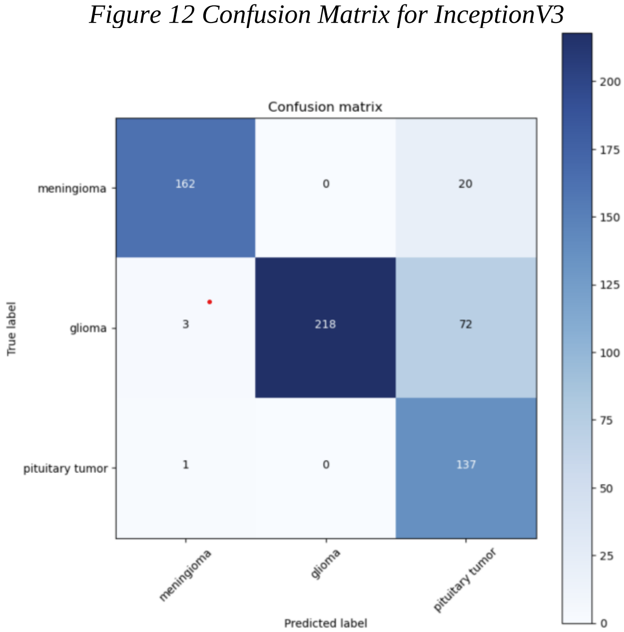

Figure 13 Confusion Matrix for MobileNet

Above confusion matrix for the different models represents that Xception and Inception transfer learning model performs very well for all three types of tumor classes, whereas the CNN model, which we built from scratch, misclassifies all three categories. But the MobileNet model is biased towards the pituitary tumor because many glioma and meningioma tumors are misclassified as pituitary tumours. This is an astonishing result because the MobileNet model is biased towards the class with the lowest number of training samples. Generally, it has been noticed in previous studies that the model used tends to tend to the type having the highest number of training samples in the training data. But we have observed the opposite behaviour in MobileNet.

DenseNet121 from MONAI achieved an overall accuracy of 92.17% on the brain MRI images. From the loss graph, it is evident that the loss decreases with the increasing number of epochs. We have used only 25 epochs here for the experiment due to resource and time limitations. The AUC(Area Under Curve) for ROC (Receiver operating characteristic) curve also increases with the number of epochs, representing an improvement in the model's ability to distinguish between the positive and negative classes. The DenseNet121 has the potential to classify better as the graph is not getting stagnant with the number of epochs. From the validation loss graph and experiments with other transfer learning models, if we increase the number of epochs to 50 or 60, we might see validation loss goes further down to 0.02. Along with it, ROC AUC should also increase.

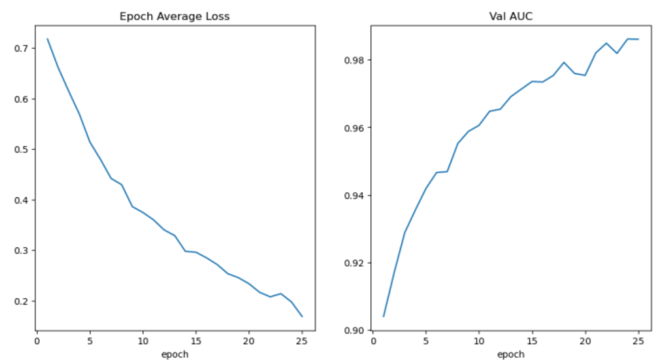

Figure 14 Loss And AUC for DenseNet121

	precision	recall	f1-score	support
2	0.9205	0.9488	0.9345	293
3	0.9672	0.9725	0.9699	182
1	0.8594	0.7971	0.8271	138
accuracy			0.9217	613
macro avg	0.9157	0.9061	0.9105	613
weighted avg	0.9206	0.9217	0.9208	613

Figure 15 Results of DenseNet121

From the above classification report, we can observe that model is biased toward the class having the highest number of training samples. Class 3 has the highest number of training samples, so precision, recall, and F1-score are also high among all three types, which suggests that the model performs the best for this class. Class 1 has the lowest number of training samples; therefore, its precision, recall, and F1 score are also the lowest among all three types. This suggests that the DenseNet121 model is leaning the classification features proportion to the number of training samples available for each class.

5. CONCLUSION AND FUTURE WORK

We have successfully implemented the various brain tumor detection classifier using CNN, transfer learning models and DenseNet121 based on MONAI. Xception was the best among all, with an accuracy of 96.41%.

In the context of improving our convolutional neural network (CNN) model developed from scratch, our model currently has approximately 13 million trainable parameters, resulting in relatively lower accuracy when compared to transfer learning models. As a possible future direction for improvement, we propose introducing additional convolutional layers followed by max-pooling layers to reduce input image size and introducing a dense layer at the end to reduce the number of parameters. This approach would increase the depth of our CNN model while reducing the number of trainable parameters, potentially leading to higher accuracy and a reduction in training computational cost.

To extend our experiments using the DenseNet121 model, we propose increasing the number of epochs and conducting experiments until the optimum accuracy is achieved. Additionally, we have identified the presence of bias towards the class with more training samples in many of our models. To address this issue, we propose modifying the data augmentation process to generate more samples for the class with fewer training samples. We also suggest implementing resampling techniques such as random oversampling, random undersampling, and SMOTE (Synthetic Minority Over-sampling Technique), assigning higher weights to the underrepresented class, and using ensemble techniques. These strategies could improve the performance of our models and address the issue of class imbalance.

6. REFERENCES

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