TENCON 2021 - 2021 IEEE Region 10 Conference (TENCON)
7-10 Dec 2021. Auckland, New Zealand

Multi-Classification based Alzheimer's Disease Detection with Comparative Analysis from Brain MRI Scans using Deep Learning

Azmain Kabir*, Farishta Kabir*, Md. Abu Hasib Mahmud*, Sanzida Alam Sinthia*, S. M. Rakibul Azam*, Emtiaz Hussain* and Mohammad Zavid Parvez†
*Department of Computer Science and Engineering, School of Data and Sciences,
BRAC University, Bangladesh
†Engineering Institute of Technology, Australia
Email: *azmain.kabir@g.bracu.ac.bd, *farishta.kabir@g.bracu.ac.bd, *md.abu.hasib.mahmud@g.bracu.ac.bd,
*sanzida.alam.sinthia@g.bracu.ac.bd, *s.m.rakibul.azam@g.bracu.ac.bd,
*emtiaz.hussain@g.bracu.ac.bd, †zavid.parvez@bracu.ac.bd

TENCON 2021 - 2021 IEEE Region 10 Conference (TENCON) | 978-1-6654-9532-5/21/$31.00 ©2021 IEEE | DOI: 10.1109/TENCON54134.2021.9707313

***Abstract*—The neurodegenerative Alzheimer's Disease is the most widely recognized cause of 'Dementia' and was allegedly the 7th highest cause of death globally. Yet, there is still no conclusive test for distinguishing Alzheimer's disease. Our proposed model eliminates these challenges in a significant manner. The technique is fit for investigating and analyzing different classes in a single setting and requires significantly less previous apprehension. Several handcrafted or predefined machine learning and deep learning models have been implemented in this field of study. Our proposed multi-classification model is primarily implemented based on the Open Access Series of Imaging Studies (OASIS) data and suggests an 18-layer architecture. We have implemented a unique preprocessing approach using all three anatomical planes of the MRI scans in a single sequential model, which was also evaluated afterwards. The research also explores a comparative study among multiple and binary classes in terms of performance and efficiency. Predefined models such as InceptionV3 and VGG19 have also been brought to comparison to measure the model's reliability. Our multiclass setting shows an accuracy of over 80%, which is higher than most of the existing multi-classification models in this dataset. Moreover, the in-depth comparative study using binary classification shows a significant accuracy of over 92%, which ensures the all-around efficacy of the model.**

***Index Terms*—Keywords - Alzheimer's Disease, CNN, Multi-class, Binary Class, MRI, Deep Learning, Comparative Analysis, 18-layer, 3D Scans, OASIS-1.**

I. Introduction

Alzheimer's disease is a neurodegenerative disease that progresses over time, mostly in elderly people. Alzheimer's is regarded as the most common cause of dementia. An umbrella term for cognitive degradation. The researchers have identified different patterns in terms of gender, age, and genetic factors. The disease is named after German psychiatrist and pathologist Alois Alzheimer who first identified the condition in 1906. Studies tell us that approximately 29.8 million people were diagnosed with the disease within 2015 [1]. Moreover, the number is about 50 million as of 2020 [2]. Most people over the age of 65 are diagnosed with the disease [3]. This disease was the 7th highest reason for death globally in 2019, with a shocking number of fatal cases [4]. The disease is arguably one of the most expensive diseases regarding therapy and treatment, along with the long diagnosis process. The most unfortunate fact is, the cause of Alzheimer's disease is not deciphered yet. Many factors are thought to play a significant role in terms of the disease. About 70 per cent of which is regarded as genetic. Other factors that put the chances of the disease higher are severe head injuries, chronic depression, hypertension, other cognitive disorders. However, most of the existing deep learning models regarding this specific disease focus on the binary classification problems or multi classification settings with significantly low accuracy. Hence, we addressed the challenges to tackle multiple (four) classes for better categorization of the disease according to their severity level and improve the performance than most of the existing architectures regarding multi classification along with a comparative analysis.

II. Research Problems and Related Works

Authors Sivakani, R., and Ansari, G. A. (2020) proposed that they employed the OASIS longitudinal MRI dataset for classification, which comprises a dataset of brain reports from all ages of AD affected people [5]. They suggest that the data must be pre-processed by addressing issues such as missing data, inconsistent data, noisy data, incorrect data, outlier data. The research also implies that improving categorization could be done more effectively by focusing on feature extraction. Another big issue with the existing models is data loss or degradation of the brain fMRI/MRI scans that causes less accuracy. For example, authors Mahmood, R., & Ghimire, B. (2013) had used the principal component analysis and artificial neural networks for their proposed approach [6]. The multi-level automated system offers a lot of room for improvement in making an early detection system that is more easily accessible and accurate. However, they did propose that they work on the ratio of ventricle enlargement to hippocampal loss as a better way to identify. Following the deep learning-based neural network-related initiatives, feature extraction techniques are becoming increasingly popular. For example, Acharya, U. R., Fernandes, S. L., WeiKoh, J. E., Ciaccio, E. J., Fabell, M. K. M., Tanik, U. J., and Yeong, C. H. (2019) claimed a remarkable accuracy in their approach. When compared to previous approaches, this one uses four techniques [7]. Authors Islam J., Zhang Y. (2017) conducted their research on the OASIS dataset with deep learning [8].

In their multiclassification (four class) based setting, their accuracy is about 73.75% which can be improved significantly through better transfer learning models and improved preprocessing strategy for feature extraction. The model also seems biased, which should be addressed. Therefore, the core problems we have been able to address are: improving the existing algorithm of the approaches to increase the efficiency in multiclass, significantly decreasing the data loss, focusing more on the individual anatomical planes for identifying patterns caused by the disease by conducting a thorough study on this particular cross-sectional dataset.

III. Methodology

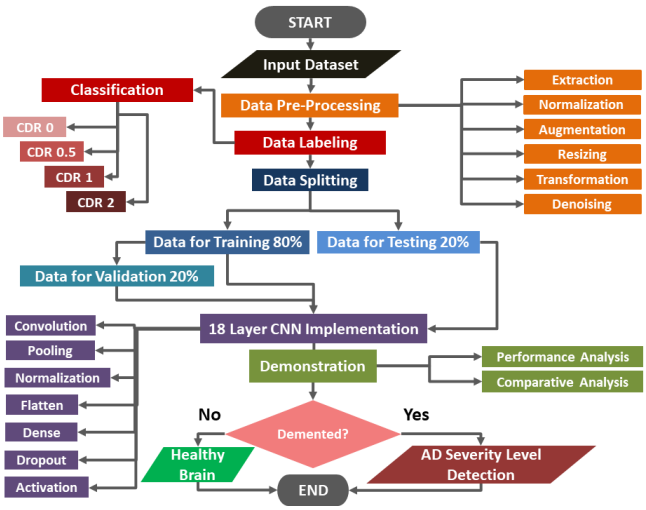

Figure 1. Proposed Model Flowchart

Our significant research has been conducted through the handcrafted preprocessing strategy. Then, a custom 18-layer approach based on convolutional neural network has been conducted in the process, which is a class of deep neural networks most commonly applied to analyzing visual imagery. The structure has been evaluated and taken under many trials, and this 18 layer architecture provides us with the most efficient and stable result comparatively. Hence, we proceeded with this proposed architecture. Lastly, we conducted a comparative study between the primary multiclass model and the binary class. We evaluated our model's performance through a comparison of the existing renowned architectures in both classifications. Our preprocessing was thoroughly evaluated by separately implementing data from the three anatomical planes and comparing it with our generalized strategy. So, our primary contributions are:

- Implementing our 18-layer architecture based on multiclass (four) classification shows a significant performance for this dataset (approximately over 80% accuracy).
- Evaluating the proposed model through two other existing architectures along with a comparative study on binary classes (Ahead in each case with approximately over 92% accuracy).
- Implementing our signature research contribution, which works with all three dimensions (brain anatomical planes) collectively through the proposed pre-processing strategy.

A. Dataset Collection

Our primary and sole dataset source is OASIS-1, which stands for Open Access Series of Imaging Studies [9]. This dataset consists of 416 subjects' cross-sectional collection. The subjects' age ranges from 18 to 96 years. About 100 of the 416 subjects are over 60, and they have very mild to severe dementia. Moreover, 20 non-demented subjects have been included in the dataset to ensure reliability. The dataset contains images of their visit within 90 days after the first session. The subjects are all right-handed and are both male and female. Each subject has two 'nii.gz' format MRI scan files, which contain several slices in each anatomical plane – sagittal, coronal, and transverse. Three or, in some cases, four individual T1-weighted MRI scans were obtained from each subject's single session.

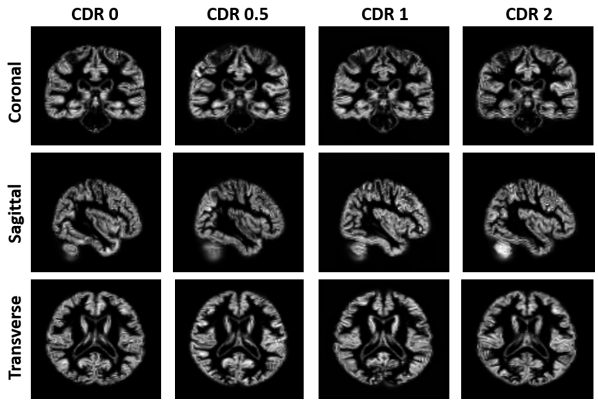

Figure 2. Anatomic Planes in Four Classes

B. Data Pre-processing

The data pre-processing step is the highlight of the proposed methodology. First of all, we extracted our image files and implemented pre-processing parameters. The OASIS-1 dataset consists of 2 cross-sectional MRI scan files per patient. The file formats are in 'nii.gz', which is the default MRI scan format. We dissected the MRI scans using the 'MRIcro software' to better study the anatomical dimensions of the scans. Each scan includes slices based on the three anatomical planes (sagittal, coronal, and transverse). The total extractable slices from each plane are $91, 109, 91$, respectively (sagittal, coronal, and transverse). Unlike most existing models' approaches, we extracted all three anatomical plane-based slices from each sample. Here, the files were segmented based on their labelling process, which coincides with the preprocessing. Initially, we found 270, 140, 56, and 4 MRI scans from CDR 0, CDR 0.5, CDR 1, and CDR 2, respectively. Then the dataset is normalized for further balancing in the four classes, respectively. To normalize and make the dataset balanced, we considered 1 slice each from the three planes (CDR 0), 2 slices from the three planes (CDR 0.5), 5 slices from the three planes (CDR 1), Sagittal: 58 slices, Coronal: 66 slices, Transverse: 49 slices for per MRI Scan (CDR 2). The dataset was further processed using a programmed approach by eliminating the obsolete images or blank slices within a certain trivially determined range. So, the total slices after normalization were 798 for CDR 0, 822 for CDR 0.5,

785 for CDR 1, 692 for CDR 2. Lastly, we conducted data augmentation for better and more precise training purposes. Ultimately, the total amount stands at – **Class 1:** 9,942 (from 270 files) **Class 2:** 10,003 (from 140 files) **Class 3:** 9,913 (from 56 files) **Class 4:** 9,645 (from 4 files). It ends up in a total of 39,503 image data to work with from 416 MRI samples. The normalization and randomization, along with augmentation, ensure unbiased training for all classes. It ultimately helps to prevent data loss and low accuracy while implementing the algorithm. The data splitting occurs right

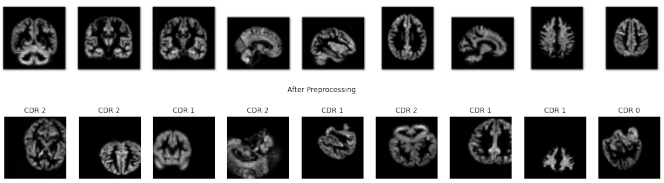

Figure 3. Before and After Pre-processing (Random Samples)

after pre-processing and labelling. Resizing, denoising has been conducted for preparing the slices for the next process. This improved the training phase of the dataset significantly.

C. Data Labeling

The multiple classes assist in detecting the presence of Alzheimer's Disease and categorize the disease in a precise way. Our labelling was done after the pre-processing phase of the dataset. CDR 0 corresponds to a healthy brain, and CDR 0.5, CDR 1 and, CDR 2 correspond with Alzheimer's Disease and the severity level.

Table I
DATA CLASSIFICATION

Label	Corresponding State
Clinical Dementia Ratio (CDR) 0	Non-demented
Clinical Dementia Ratio (CDR) 0.5	Mild Demented
Clinical Dementia Ratio (CDR) 1	Moderately Demented
Clinical Dementia Ratio (CDR) 2	Severely Demented

D. Data Splitting

The data segmentation or splitting and the pre-processing were conducted simultaneously. The entire dataset was split into 80% and 20% for training data and testing data, respectively, based on an 8:2 ratio randomly. Moreover, later on, 20% of the training data was used for validation purposes. The split datasets have a batch size of 32 each, and the target size is (64, 64).

E. Proposed 18-layer Convolutional Neural Network (CNN) Model Architecture

Our proposed model consists of 18 layers and seven steps individually. The steps of the architecture have been explained below:

- **Convolutional Layer:** Our proposed CNN architecture consists of three Conv2D. Conv2D is used as a mandatory parameter that determines how many convolutional layers the network will learn. In this case, the number is three.
- **Pooling Layer:** In our model, the three MaxPooling2D layers correspond with the three Conv2D layers we have implemented, which is responsible for calculating the largest or maximum value of the feature map.
- **Batch Normalization:** Our architecture has two batch normalization layers. These help the entire network learn more independently and normalize the output each previous layer offers. Using batch normalization also helps to standardize the output and input layers in sequential models.
- **Flatten Layer:** We have two flatten layers in the sequential model that helps to flatten the output by creating a single long feature vector in the convolutional layers. The flatten layer is also connected with the ultimate classification model known as the fully connected layer.
- **Dense Layer:** The architecture has seven dense layers, and a dense layer passes on the outputs from its previous layers to the subsequent neurons, and each neuron provides an output to the next layer.
- **Dropout:** In our proposed architecture, the dropout layer is used to prevent our model from overfitting.
- **Activation Function:** The sequential model architecture uses 2 activation functions - Rectified Linear Unit or ReLU and Softmax. ReLU is a piecewise linear function that provides an output straight away when positive, or it will give an output of zero. On the other hand, the Softmax function takes the previous layer's numeric output in a multiclass classification-based neural network. It transforms it into probabilities by using the exponents of each output. Then the values are normalized one by one according to the sum of the exponents. The activation functions are shown as follows:

ReLU:

$$a = max(0, x) \tag{1}$$

Softmax:

$$\sigma(\vec{z_i}) = \frac{e^z i}{\sum_k^{j=1} e^{zj}} \tag{2}$$

Table II
A SUMMARY OF OUR PROPOSED 18 LAYER CNN MODEL

Layer	Output Shape	Param #
conv2d	(None, 80, 80, 25)	1900
max_pooling2d	(None, 40, 40, 25)	0
conv2d_1	(None, 20, 20, 50)	31300
max_pooling2d_1	(None, 10, 10, 50)	0
batch_normalization	(None, 10, 10, 50)	200
conv2d_2	(None, 5, 5, 70)	31570
max_pooling2d_2	(None, 2, 2, 70)	0
batch_normalization_1	None, 2, 2, 70)	280
flatten	(None, 280)	0
dense	(None, 100)	28100
dense_1	(None, 100)	10100
dropout	(None, 100)	0
flatten_1	(None, 100)	0
dense_2	(None, 32)	3232
dense_3	(None, 32)	1056
dense_4	(None, 32)	1056
dense_5	(None, 32)	1056
dense_6	(None, 4)	132

IV. Implementation and Result

A. Demonstrating the performance of our proposed model (Multiclass)

The implementation starts from running our proposed sequential model by training and testing the data epoch by epoch. Here we considered 50 epochs while running the model. We have considered five metrics to evaluate our model's performance – accuracy, precision, recall, F1 score, and AUC. We have also implemented a separate function to handle the exponential decay. The equations of accuracy, F1-score, precision, and recall are shown as follows:

Accuracy Equation:

$$ACC = \frac{TP + TN}{P + N} = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

F1 Score:

$$F1 = 2 \times \frac{PPV \times TPR}{PPV + TPR} = \frac{2TP}{2TP + FP + FN} \tag{4}$$

Precision:

$$PPV = \frac{TP}{(TP + FP)} = (1 - FDR) \tag{5}$$

Recall Equation:

$$PPV = \frac{TP}{(TP + FP)} = (1 - FDR) \tag{6}$$

Where (in equations (3) to (6)), ACC = Accuracy, TP = True Positive, TN = True Negative, PPV = Positive Predictive Value/Precision, PPV = Positive Predictive Value/Precision, TPR = True Positive Rate, FDR = False Discovery Rate,TP = True Positive, FN = False Negative, P = Condition Positive, N = Condition Negative

B. Result Analysis (Multiclass):

Accuracy: The history of the accuracy graph depicts the training and validation process accuracy. It indicated the number of correct predictions by the model. The training data accuracy is favourable for this initial version of the proposed model, about 80%. But the validation data lags slightly to match up to the accuracy bar, which is about 79%. So, the difference is around 1% in terms of the accuracy graph.

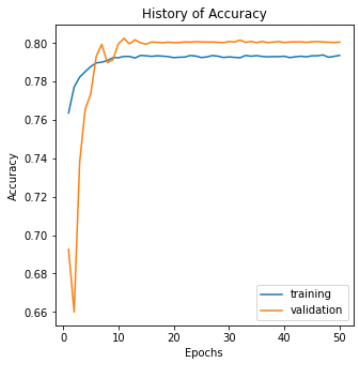

Figure 4. History of Accuracy (Multiclass)

Precision: The graph shows that the training phase has ensured precision of about 62-63%, which has scopes for improvement in further studies regarding this data set in multi-class. The validation data is close to the training data, which is also around 62%.

Loss: The loss curve indicates the errors made by the model. It shows how much data is being hampered in terms of precision and decreasing true positive and true negative results in some cases. This can play a role in providing faulty results in testing. The training loss is within the 1 to 1.5 range.

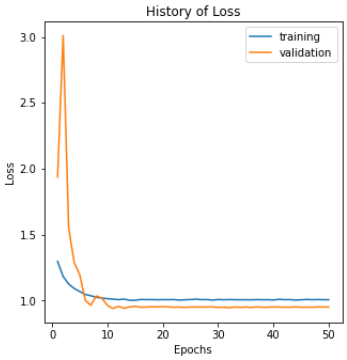

Figure 5. History of Loss (Multiclass)

Recall: Higher recall means the model's capability to detect the positive samples successfully. It is the ratio between the number of correctly classified positive samples and the total number of positive samples. The recall of the model is about 24.72%.

AUC: The Area Under the Curve or AUC graph summarizes the Receiver Operating Characteristic or ROC curve in a specific model. It depicts the ability to distinguish between the positive and negative classes. The AUC in our proposed model is about 80-81% in the training data and about 79-80% in the validation data. This ensures that the AUC works well in this model, but it can be spiked up even higher with further improvement.

F1-Score: The F1-score in our proposed model is about 36-37% in terms of training and around 33-34% mainly in terms of validation data. The F1 score gets low due to low precision and recall value. Our precision and recall values are about 85.80% and 24.72%, respectively. This explains why the F1-score is minor in this regard which is about 37.73%.

C. Comparative Result Analysis (Multiclass: Separate Anatomical Planes):

As we mentioned, the preprocessing strategy considers all the anatomical planes such as sagittal, coronal, and transverse rather than many existing approaches where a single anatomical plane is taken under consideration while preprocessing and implementing the model. Hence, we conducted a comparative analysis on all three separate anatomical planes available on the dataset, preprocessed it in the same manner, and compared the result with the proposed preprocessing strategy.

D. Loading Pre-trained Convolutional Neural Network (CNN) Models and Comparative Result Analysis (Multiclass)

A model's sustainability and efficiency can only be evaluated through its performance evaluation compared to the

Table III
THE COMPARISON AMONG THE SEPARATE ANATOMICAL PLANE BASED DATA AND THE PROPOSED COMBINED PREPROCESSED DATA (MULTICLASS)

Ana. Plane	Accuracy	Precision	Recall	AUC	F1-Score
Sagittal	82.35%	78.92%	40.15%	87.23%	52.86%
Coronal	80.66%	86.97%	26.64%	84.00%	40.53%
Transverse	79.22%	67.74%	32.23%	81.74%	43.30%
Combined	80.09%	85.80%	24.72%	81.89%	37.73%

predefined and pre-trained existing models. We considered some of the most well-known existing models to compare our approach with - InceptionV3 and VGG19 architecture. The InceptionV3 architecture has been further analyzed in comparison to the other renowned architectures mentioned above in the research work by authors Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J., & Wojna, Z. (2016) in their literature 'Rethinking the Inception Architecture for Computer Vision' [10]. An extensive study based on AD detection using VGG architecture has been conducted in the research of authors Adeola Ajagbe, Kamorudeen A. Amuda, Matthew A. Oladipupo, Oluwaseyi F. AFE & Kikelomo I. Okesola (2021) [11].

E. Comparison among the proposed model and the pre-trained CNN models (Multiclass)

Table IV
THE COMPARISON AMONG THE PREDEFINED MODEL(S) AND THE PROPOSED MODEL (MULTICLASS)

Models	Accuracy	Precision	Recall	AUC	F1-Score
Proposed Model	80.09%	85.80%	24.72%	81.89%	37.73%
InceptionV3	78.91%	95.18%	16.47%	77.35%	27.62%
VGG-19	77.66%	58.48%	36.67%	81.55%	45.05%

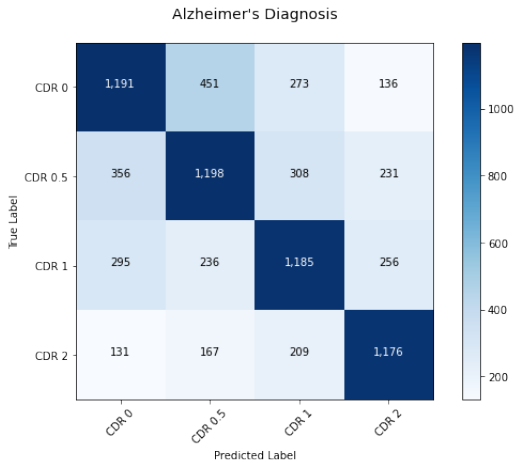

Figure 6. Confusion Matrix (Multiclass)

Here, if we further analyze the result, we can observe that the accuracy of our proposed model is about 80.09%, whereas the InceptionV3 architecture shows a very similar 78.91% accuracy. The result is 1.18% higher, which is very close to the pre-trained model, and we can conclude that the result is almost equal in this regard. Then comes the precision, which is about 85.80% in our model and 95.18% in the mentioned architecture. In this regard, the InceptionV3 architecture performs slightly better than the proposed model. The recall is higher in our proposed model, about 24.72%, and the InceptionV3 has about 16.47%. So, our model works better in terms of recall metrics. Then comes the AUC. AUC in our proposed model is 81.89%, and the pre-trained model is about 77.35% which ensures that our AUC value is higher in our model. The F1-score is also quite similar as both are about 37.73% and 27.62%, respectively. On the other hand, the VGG19 architecture falls short in almost all the metrics except the recall value and F1-score. The accuracy, precision, recall, AUC, F1-score are 77.66%, 58.48%, 36.67%, 81.55%, 45.05% respectively. These existing models, in most cases, serve higher performance than vanilla CNN. Transfer learning models VGG and InceptionV3 are quite renowned, but they have shortcomings in some metrics and generalized cases. In contrast, our proposed model ensures a custom-made 18-layer approach that improves computational time and accuracy efficiency as it was trained under all possible cases for such datasets. Hence, the validation data and the training data show impressively similar performance on the record.

F. Comparison among the proposed model and the pre-trained CNN models and Comparative Result Analysis (Binary Class):

We have also implemented our model in terms of binary class to show the efficiency of the model [12]. The binary classes we considered were CDR0 and CDR2.

Accuracy: The accuracy of the training data is almost 92.78%, which is a significant indication of the model's efficiency. The validation dataset stabilizes around 90%.

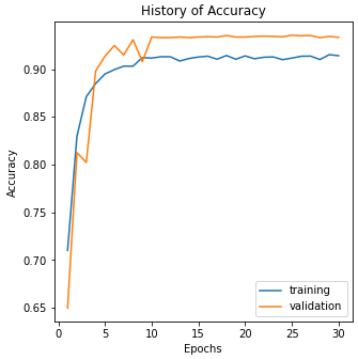

Figure 7. History of Accuracy (Binary Class)

Loss: The binary classification shows the loss value starts and finishes within the range of 0.6 to almost 0.25 gradually in terms of training data. And, the validation data jumps around the range of 0.7 to 0.2.

From the statistical values, we can observe that our model has also shown significant performance strength in binary class. The accuracy of the proposed model and the InceptionV3 is quite similar in binary class, but VGG19 falls short strikingly.

V. CONCLUSION AND FUTURE WORKS

Our model has shown impressive strength in each comparative case. As most of the existing models work with binary

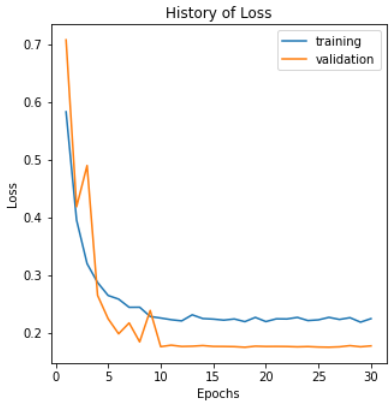

Figure 8. History of Loss (Binary Class)

Table V
THE COMPARISON AMONG THE PREDEFINED MODEL(S) AND THE PROPOSED MODEL (BINARY CLASS)

Models	Accuracy	Precision	Recall	AUC	F1-Score
Proposed Model	92.78%	92.78%	92.78%	97.88%	92.83%
InceptionV3	91.32%	93.64%	89.93%	96.86%	87.56%
VGG-19	50%	50%	25%	50%	33.5%

classifications and specific MRI planes, we had considered extending the multiple classification research ahead. In the future, further extension can be done by ensuring improved algorithms to enhance accuracy. The dataset also had some shortcomings in unbalanced data in all four classes, which we tried to overcome with our handcrafted preprocessing strategy. We are hopeful of receiving much significant performance in other datasets in the future and plan to work on the different datasets to ensure our model's versatility further. We can implement a clustering process, improved loss functions, and K-fold class validation for better testing validation results to improve the architecture. Moreover, we desire to introduce a medical web application platform for real-time AD Detection implementing our improved architecture. This will help detect the disease at a premature stage without any manual assistance to limit the chance of making further complications of the hard to fathom Alzheimer's disease patients.

VI. ACKNOWLEDGEMENT

The research has been conducted on the OASIS-1 dataset. This project is supported by grants P50 AG05681, P01 AG03991, P01 AG026276, R01 AG021910, P20 MH071616, U24 RR021382.

REFERENCES

[1] T. Vos, C. Allen, M. Arora, R. M. Barber, Z. A. Bhutta, A. Brown, A. Carter, D. C. Casey, F. J. Charlson, A. Z. Chen, *et al.*, "Global, regional, and national incidence, prevalence, and years lived with disability for 310 diseases and injuries, 1990–2015: A systematic analysis for the global burden of disease study 2015," *The lancet*, vol. 388, no. 10053, pp. 1545–1602, 2016.

[2] W. H. Organization *et al.*, *Dementia fact sheet world health organization*, 2018.

[3] C. V. Balaji, M. B. LR, and M. L. Hingane, "Alzheimer's disease progression & treatment," 2021.

[4] H. Wang, M. Naghavi, C. Allen, R. M. Barber, Z. A. Bhutta, A. Carter, D. C. Casey, F. J. Charlson, A. Z. Chen, M. M. Coates, *et al.*, "Global, regional, and national life expectancy, all-cause mortality, and cause-specific mortality for 249 causes of death, 1980–2015: A systematic analysis for the global burden of disease study 2015," *The lancet*, vol. 388, no. 10053, pp. 1459–1544, 2016.

[5] R. Sivakani and G. A. Ansari, "Machine learning framework for implementing alzheimer's disease," in *2020 International Conference on Communication and Signal Processing (ICCSP)*, IEEE, 2020, pp. 0588–0592.

[6] R. Mahmood and B. Ghimire, "Automatic detection and classification of alzheimer's disease from mri scans using principal component analysis and artificial neural networks," in *2013 20th International Conference on Systems, Signals and Image Processing (IWSSIP)*, IEEE, 2013, pp. 133–137.

[7] U. R. Acharya, S. L. Fernandes, J. E. WeiKoh, E. J. Ciaccio, M. K. M. Fabell, U. J. Tanik, V. Rajinikanth, and C. H. Yeong, "Automated detection of alzheimer's disease using brain mri images–a study with various feature extraction techniques," *Journal of Medical Systems*, vol. 43, no. 9, pp. 1–14, 2019.

[8] J. Islam and Y. Zhang, "A novel deep learning based multi-class classification method for alzheimer's disease detection using brain mri data," in *International conference on brain informatics*, Springer, 2017, pp. 213–222.

[9] D. S. Marcus, T. H. Wang, J. Parker, J. G. Csernansky, J. C. Morris, and R. L. Buckner, "Open access series of imaging studies (oasis): Cross-sectional mri data in young, middle aged, nondemented, and demented older adults," *Journal of cognitive neuroscience*, vol. 19, no. 9, pp. 1498–1507, 2007.

[10] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, "Rethinking the inception architecture for computer vision," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2016, pp. 2818–2826.

[11] S. A. Ajagbe, K. A. Amuda, M. A. Oladipupo, O. F. AFE, and K. I. Okesola, "Multi-classification of alzheimer disease on magnetic resonance images (mri) using deep convolutional neural network (dcnn) approaches," *International Journal of Advanced Computer Research*, vol. 11, p. 53, 2021.

[12] E. Hussain, M. Hasan, S. Z. Hassan, T. H. Azmi, M. A. Rahman, and M. Z. Parvez, "Deep learning based binary classification for alzheimer's disease detection using brain mri images," in *2020 15th IEEE Conference on Industrial Electronics and Applications (ICIEA)*, IEEE, 2020, pp. 1115–1120.