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Borderline Personality Disorder Detection by Image Signal Processing and Machine Learning Techniques

Sherif Medhat[1,*], **Hesham H. Aly**[1] **and Medhat A. El-messiery**[2]

[1]Arab Academy for Science, Technology and Maritime Transport, Egypt

[2]Basic Science Department, Higher Engineering Institute, Thebes Academy, Cairo, 11434, Egypt

[*]**Corresponding Author:** Sherif Medhat, Arab Academy for Science, Technology and Maritime Transport, Egypt, Tel: +201015799419, E-mail:sherifffmedhattt@gmail.com

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Abstract

Borderline Personality Disorder (BPD) is a complex mental illness characterized by emotional dysregulation, impulsivity, and unstable relationships. Despite its significant impact, BPD remains challenging to diagnose accurately. This paper explores the potential of image signal processing and machine learning (ML) using MRI imaging data to improve BPD classification. Different digital filters with conventional neural networks are used. Distinction between normal and BPD patients was carried out and the results showed that with no filter the prediction of the disease had an accuracy of 92.74%, while using low pass filter accuracy 89.42% was reached. Finally, the high pass filter achieved accuracy of 96.68%.

Keywords: Borderline Personality Disorder; Image Processing; Fast Fourier Transform; Digital Filters; Machine Learning

List of Abbreviation

BPD - Borderline Personality Disorder; DSM - Diagnostic and Statistical Manual of Mental Disorders; MRI - Magnetic Resonance Imaging; ML - Machine Learning; FFT - Fast Fourier Transform; AI - Artificial Intelligence; pwBPD - People with Borderline Personality Disorder; SCID - Schedule for Clinician Assessment of Neuropsychiatric Disorders; UCLA - University of California, Los Angeles; CNN: Convolutional Neural Network; ReLU: Rectified Linear Unit (common activation function in CNNs, you can add this if applicable); Softmax: Softmax function (used in the final layer for multi-class classification) epochs: Epochs (training iterations); TP - True Positive (count value in confusion matrix); TN - True Negative (count value in confusion matrix); FP - False Positive (count value in confusion matrix); FN - False Negative (count value in confusion matrix); AUC-ROC - Area Under the Receiver Operating Characteristic Curve

Introduction

Borderline Personality Disorder is a serious mental disease, classified in Cluster B of DSM IV-TR personality disorders (BPD). BPD is a mental illness characterized by mood swings, extreme fear of abandonment, impulsivity, unstable relationships and unstable self-image [1]. Therefore, it affects the way the person feels and think. Previous research estimated the prevalence of borderline personality disorder to be 1.6% in the general population [2].

Although the cause of borderline personality disorder is uncertain. The main problem with the Borderline personality disorder is that it's hard to diagnose and can get misdiagnosed due the overlapping with its symptoms with other mental illnesses like bipolar and narcissistic personality order [1]. Plus, diagnosing BPD early allows individuals with BPD to access treatment strategies like therapy and medication management sooner. Research suggests this can significantly improve long-term outcomes and quality of life and reduces risk of self-harm and suicidal behaviors and the case can worsen over time. Moreover, if BPD got misdiagnosed patients will not relieve the appropriate treatment they need to manage their symptoms.

Therefore, many papers tried to build models to diagnose and detect pattern to differentiate between people with borderline personality disorder(pwBPD) from normal. For, example, some used image processing, signal processing and machine learning detect the BPD pattern. In general, the reported accuracy of distinction between normal and BPD never exceeded 93%. However, the origins on this serve personality disorder remains challenging.

It was noted that there's differences between the brain structure and activity of the pwBPD and the normal [3]. Previous research has found that patients with BPD have smaller brain areas and unusual activity levels. The difference was detected in mainly three part of the brain [3]. Firstly, the amygdala which plays an important role in regulating emotions. Secondly, the hippocampus which helps regulate behavior and self-control. Lastly, the orbitofrontal cortex – which is involved in planning and decision making [4].

Aim

In this work an artificial intelligence (AI) model that can differentiate between a patients with BPD and the normal person according to their MRI using image processing and machine and deep learning techniques was introduced. Getting to know whether the AI model will be able to identify differences between the brain structure of patients with BPD from normal. The main previous researchers decided to use AI is to investigate and classify the BPD is that AI models can learn complex patterns in image data. The differentiation is based on accuracy, precision, Sensitivity, Specificity and confusion matrix. Moreover, models can be scaled to process large volumes of images quickly and efficiently and models can be trained to be robust to noise and variations in image quality.

Dataset

The dataset of patients with BPD were selected from Clinical Research Imaging Centre in Edinburgh (OpenNeuro database, accession number ds000214) [8,10]. The MRI data of control were selected from UCLA Consortium for Neuropsychiatric Phenomics (OpenNeuro database, accession number ds000030) [8,11]. We selected 20 patients with BPD and 20 participants for control who were recruited via community advertisements in the Los Angeles area. Self-reported history of psychopathology was verified with the SCID-IV [9]. Inclusion criteria comprised the following: at least 8 years of education, no history of head injury with loss of consciousness or cognitive sequelae, no use of psychoactive medications or substance dependence within past 6 months, and no history of major mental illness. Participants were excluded if they had history of significant medical illness, contraindications for MRI, and mood-altering medication on scan day (based on self-report). All participants gave written informed consent approved by the University of California, Los Angeles Institutional Review Board. The MRI was obtained using a 3T Siemens Magneton Verio with TR = 2,300 (ms), TE = 2.98 (ms), and 160 slices [8]. All the above methods were carried out in accordance with relevant guidelines and regulation and the experimental protocols were approved by a University of California, Los Angeles Institutional Review Board.

Data Preprocessing

After checking all the MRI images to make sure they are free from errors. We starting by transforming each of them into greyscale images so each MRI is now a 2D matrix.Then we normalized each of the MRI images to ensures optimal comparisons across the data. Then we resized each MRI image to be of dimension [240,256].

Proposed Model

Firstly, a primarily work deep learning model without filtration was apply to the MRI data as shown in Figure 1. A Convolutional Neural Networks (CNN)of size (120, 128, 32) were used to fit our MRI and depth of 3 layers. Followed by multiple neural networks layers to improve the accuracy and precision and the ability of the model to understand more complex data. Finally, a softmax layer to make the final decision. A learning rate of 0.000005 and 50 epochs were used. The CNN is used with images as the act as feature extracting method which reduces the need for extensive image pre-processing, a common step in traditional computer vision tasks. This saves time and allows the model to focus on learning the most relevant features from the data itself. Figure 2 shows the MRI image example without any filters added.

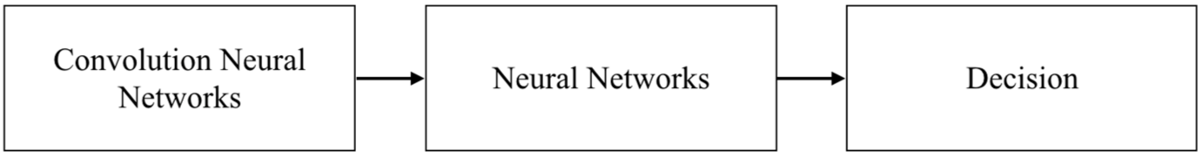

Figure 1: Flowchart shows the primary model

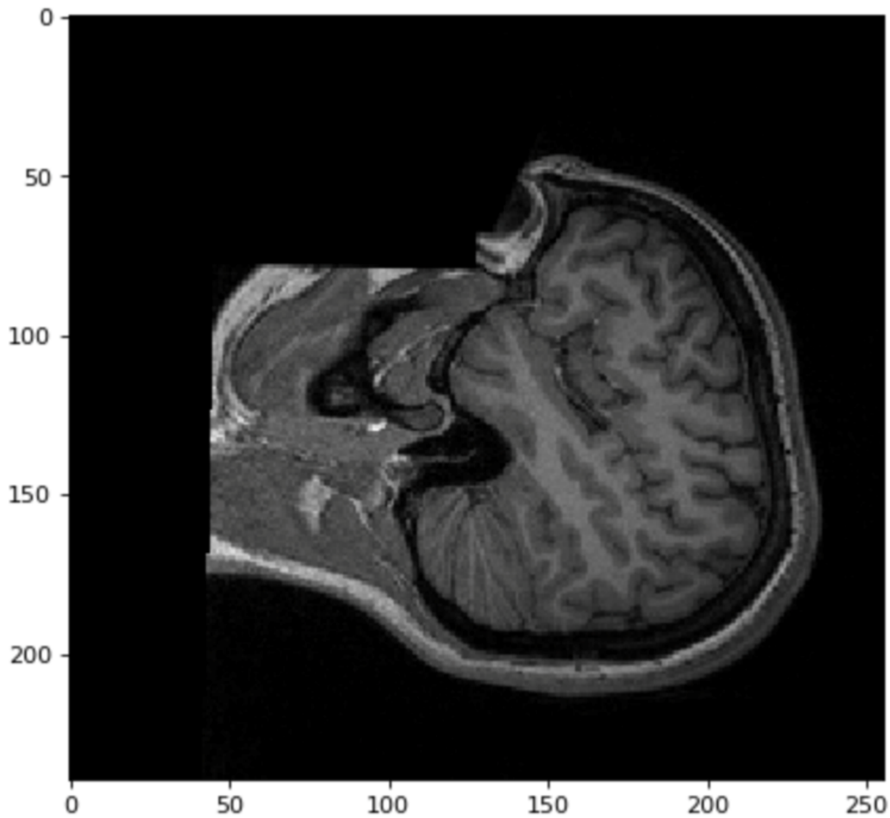

Figure 2: Shows the Mri Image in the Time Domain

Secondly, filtering was introduced to the data as shown in Figure 3, In order to improve the results we started to apply image processing techniques. By applying both low and high pass filters and then compare the results.

We first transferred the MRI matrix from the time domain to the frequency domain which is shown in Figure 4 using Fast Fourier Transform (FFT).

After transferring the MRI image to the frequency domain, we created low pass filter and applied the filter to the MRI matrix in the frequency domain with a cut off frequency of 20 Hz. Then reconstructed the MRI image from the frequency domain to the time domain using Inverse Fast Fourier Transform (IFFT). The low pass filter is used to Lowers image sharpness slightly by blurring the image Reducing unwanted artifacts patterns. The high pass filter is used to Enhances image sharpness by emphasizing edges showing more details.

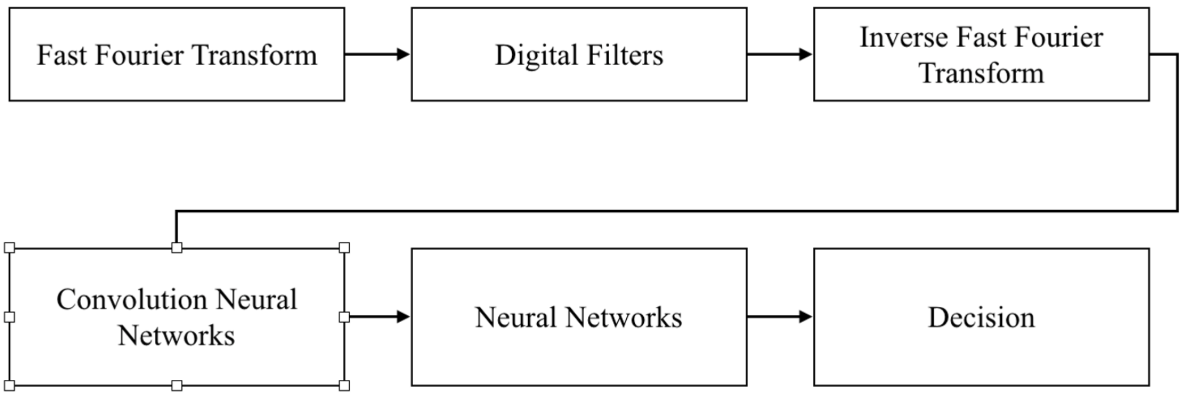

Figure 3: Shows the full model flow

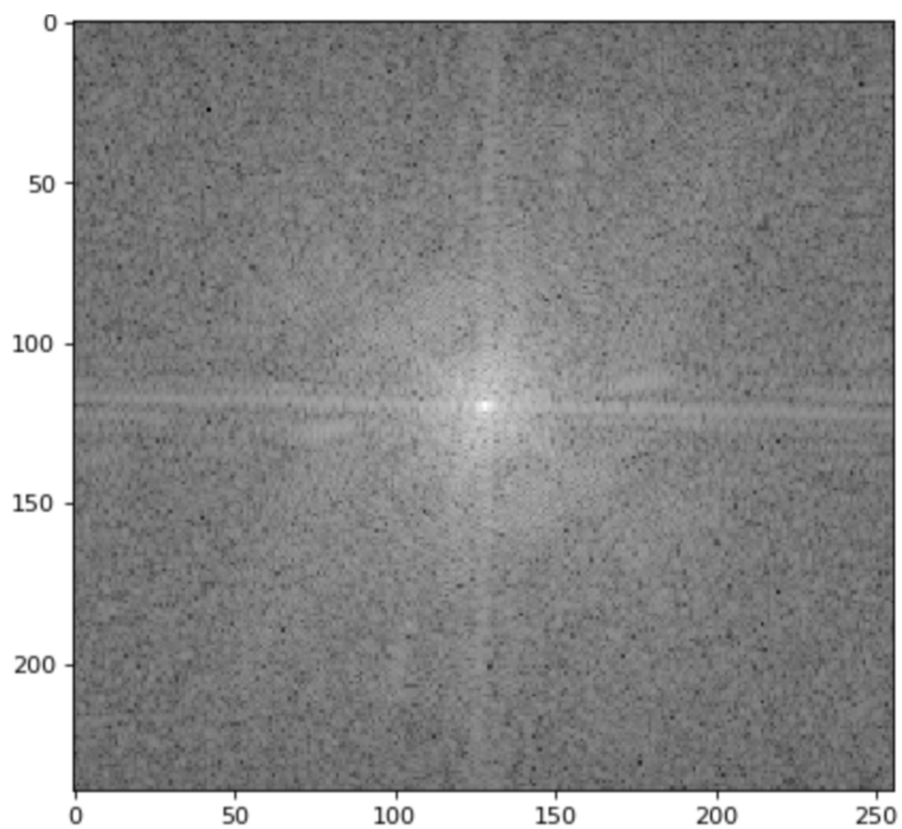

Figure 4: Shows Mri Image in the Frequency Domain

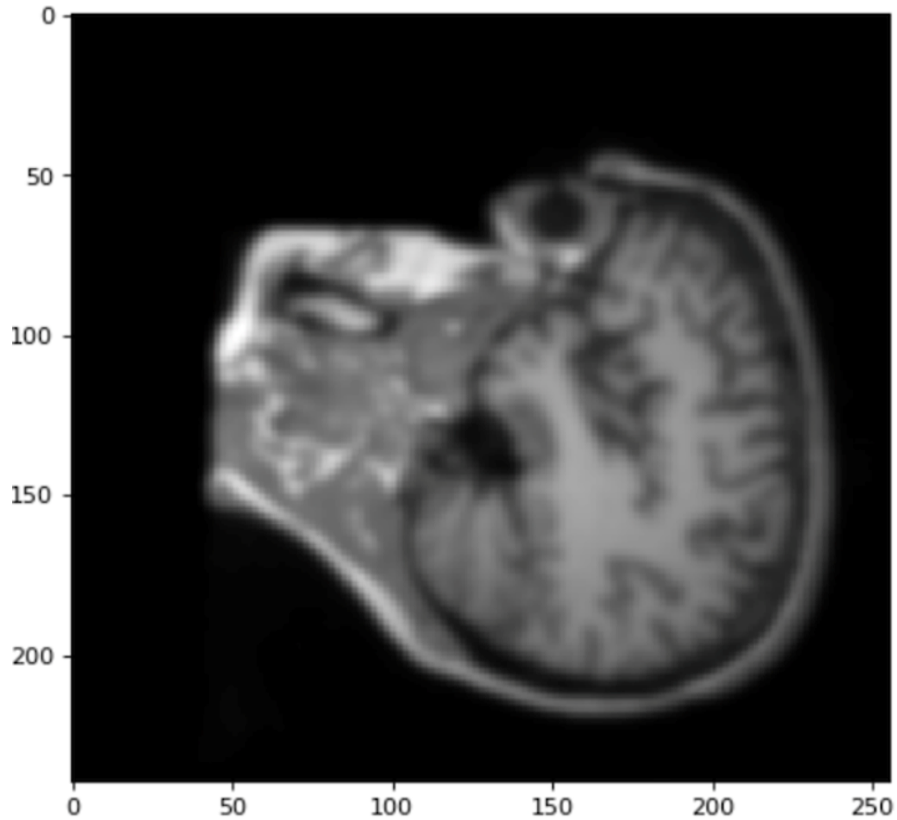

Figure 5: Shows the Mri Image After Applying the Low Pass Filter

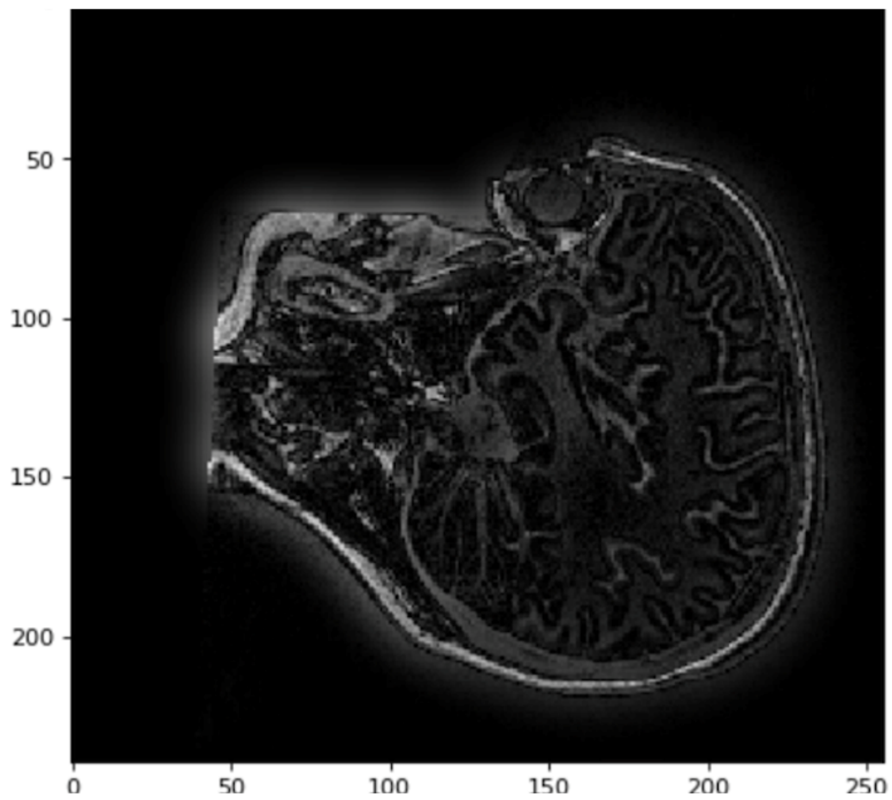

Figure 6: Shows the Mri Image After Applying the High Pass Filter

The low pass filter is often used with the MRI data as it filters the noise and help reaching better results so as we can observe from Figure 5 the image is blurry because the low pass filter.

Then we feed the model with the reconstructed filtered MRI data and start training the model using the same hyper-parameters. However, the results didn't improve as the accuracy was 0.8942.

Then we started to apply high pass filter which filters the low frequencies allowing only the high frequencies to pass so the image looks more sharp as shown in Figure6 [5]. In order to apply the high pass filter we used the MRI images in the frequency domain we got from the Fast Fourier transform.

Then we designed a high pass filtered with cutoff frequency of 5 Hz.

There was an obvious improvement in the performance of the model and the results when we used the high pass filter as the accuracy was 0.9668.

Discussion

Now we will compare the results for the three models we have created with different image processing techniques where the first one we used no filter, the second we used a low pass filter and the third we used a high pass filter.

Firstly, we compare the change of both the test and validation accuracies with the epochs for the three methods.

when the low pass filters applied it was able to filter the noise however the MRI images becomes a little bit blurry as previously mention. However, there was no much improvements as the training and test validation accuracies reached 0.8942 and 0.9622 respectively.

Then, when we applied a high pass filter which make the image sharper there was noticed improvements regarding both the training and validation accuracies reaching 0.9668 and 0.9832 respectively.

Moreover, it is clear from Figure7 and figure 8 that the model with low pass filter had an overall better performance than both the model will out filter and the model with low pass filter.

In order to validate and test the models more we tested them using the confusion matrix

A confusion matrix presents a table layout of the different outcomes of the prediction and results of a classification problem and helps visualize its outcomes [6] as shown in Figure 9.

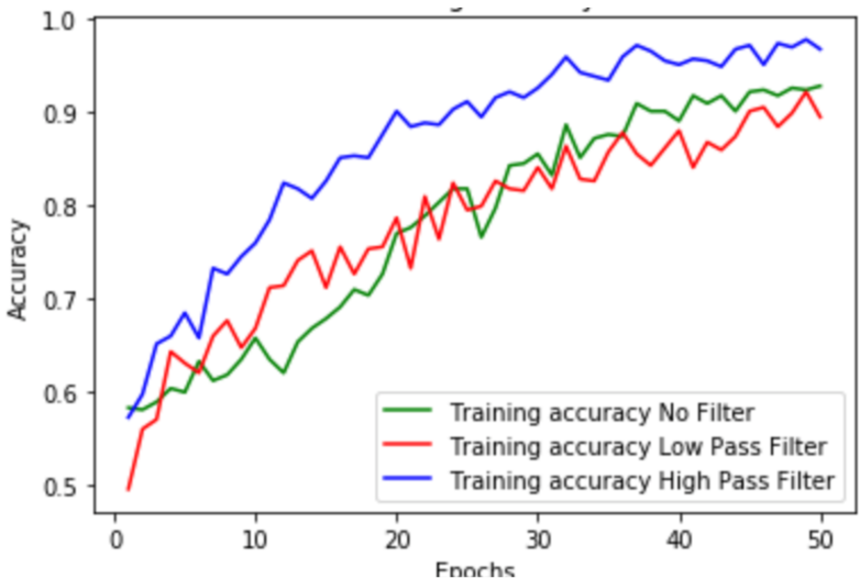

Figure 7: Training Accuracy Changes with Respect to Epochs

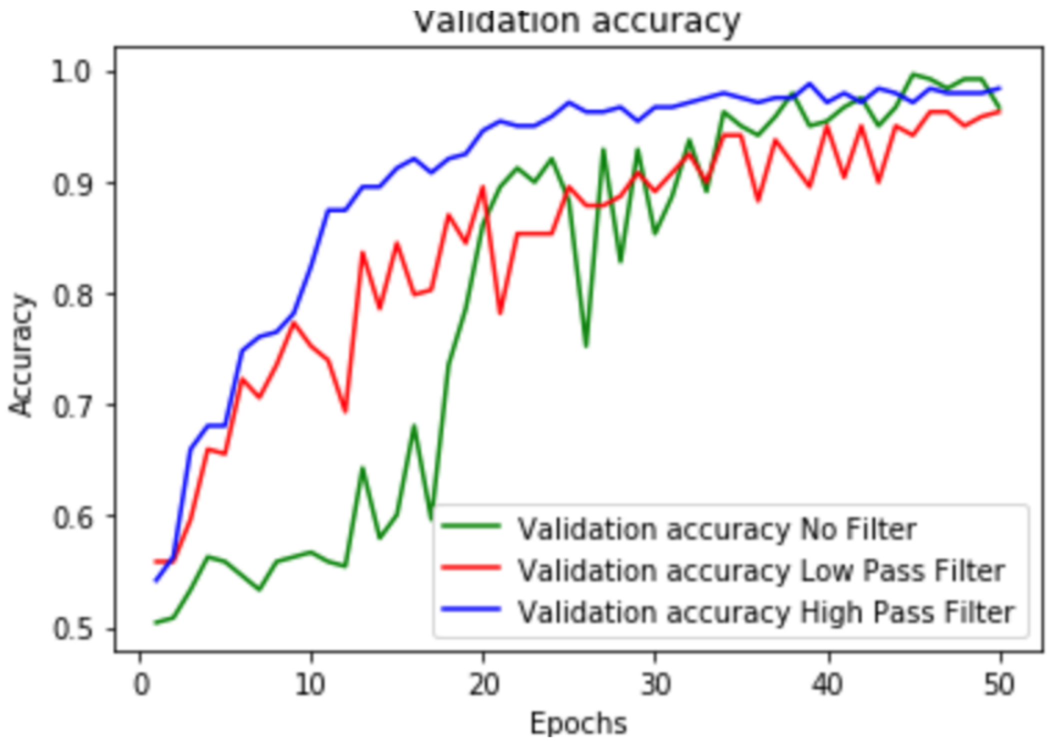

Figure 8: Validation Accuracy Changes with Respect to Epochs

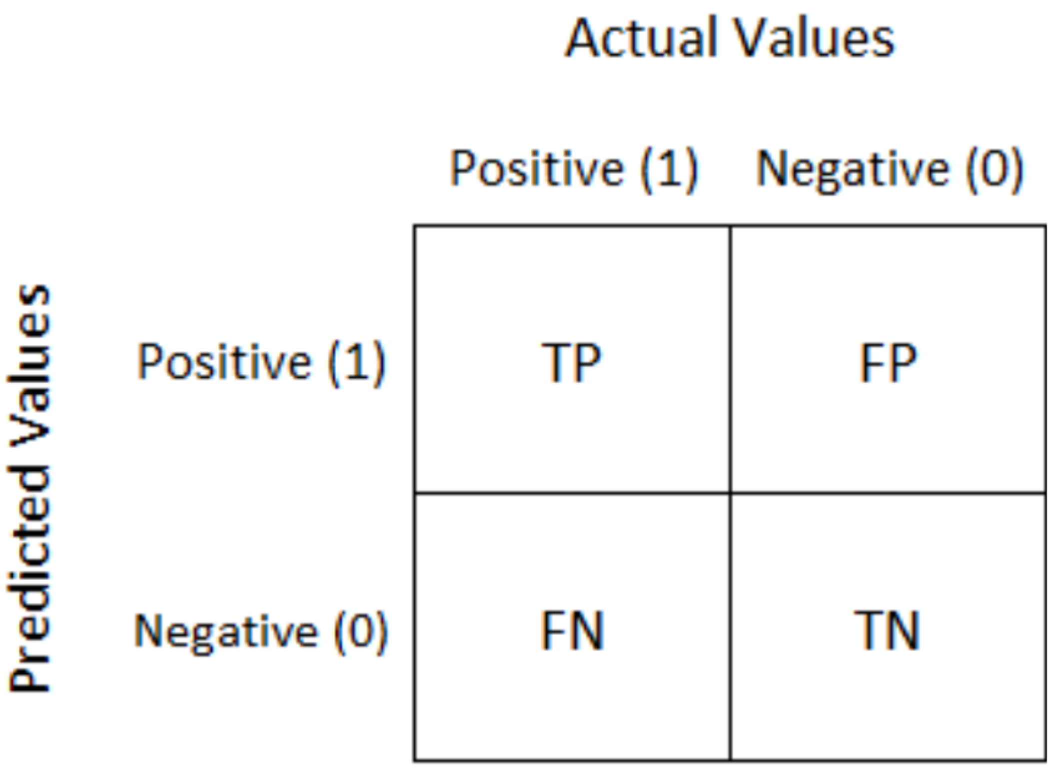

Figure 9: Shows Confusion Matrix

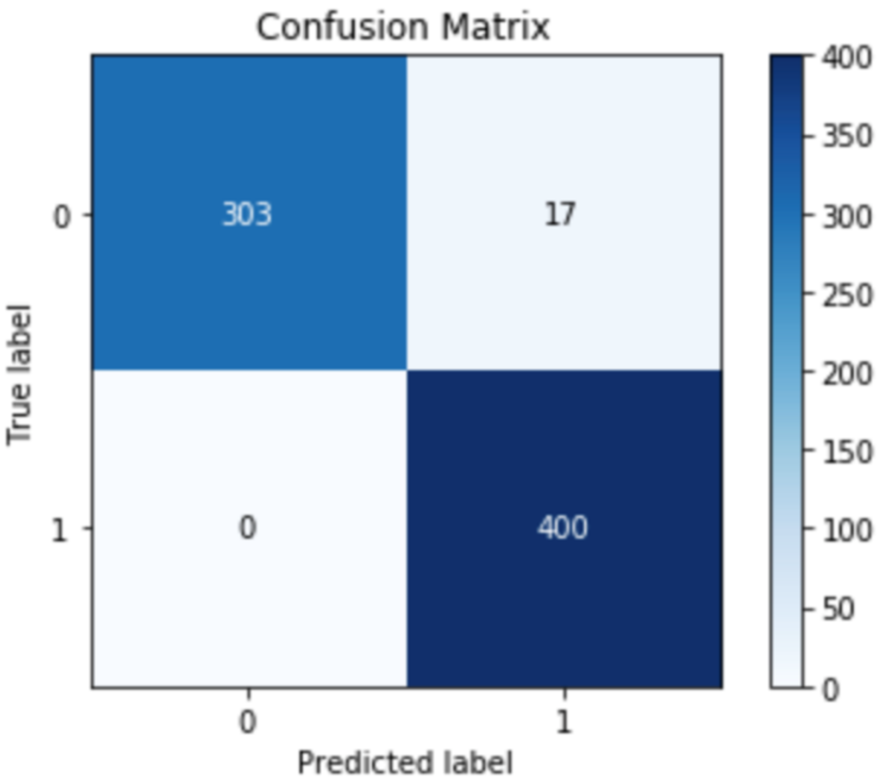

Figure10: Shows the Confusion Matrix for the Model Without a Filter

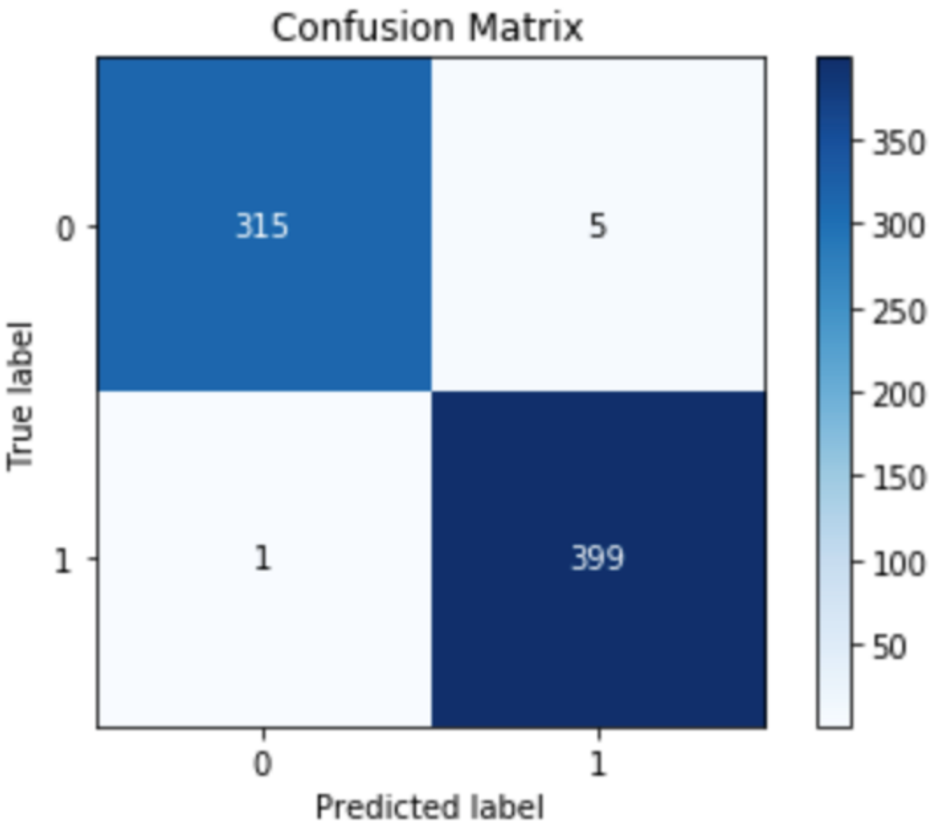

Figure 11: Shows the Confusion Matrix for the Model with High Pass Filter

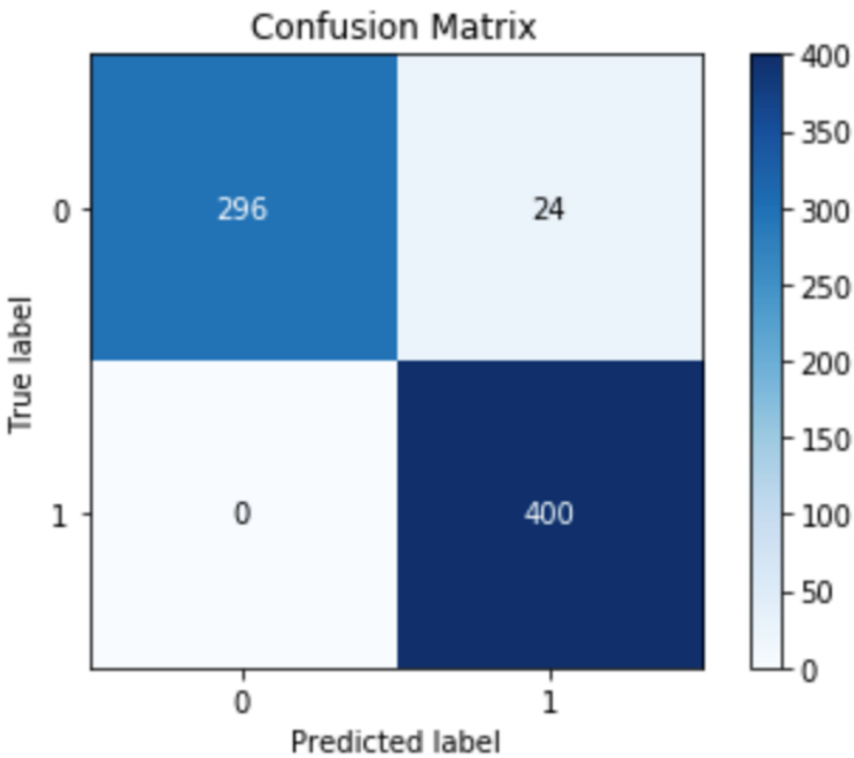

Figure 12: Shows the Confusion Matrix for the Model with Low Pass Filter

The confusion matrix is used as it shows the number of correct and incorrect predictions and that are summarized with count values and broken down by each class [6].

Therefore, it allows us to measure recall, precision, accuracy, and AUC-ROC curve. The confusion matrix of the model with no filter is shown in Fig. 10, the confusion matrix of the model with high pass filter is shown in Figure 11, the confusion matrix of the model with low pass filter is shown in Figure 12.

Firstly, the precision which measures the percentage of predictions made by the model that are correct, so it helps us to visualize the reliability of the machine learning model in classifying the model as positive [7].

$$Precision = \frac{TruePostive}{(TruePostive + FalsePostive)} \quad [7]$$

So, the model without a filter achieved precision of 0.9469, the model with low pass filter achieved precision of 0.9250

and the model with high pass filter achieved precision 0.9843.

Secondly, the sensitivity or the recall is measure of how well a machine learning model can detect positive instances.The recall is calculated as the ratio between the numbers of Positive samples correctly classified as Positive to the total number of Positive samples. The recall measures the model's ability to detect positive samples.

$$Recall = \frac{TruePostive}{TruePostive + FalseNegative} \quad [7]$$

So, the sensitivity or the recall didn’t change too much from the three models

It reached a value of 1.0 for both the model with no filter and the model using low pass filter and reached

0.9968 for the model with high pass filter.

Finally, we have the specificity which presents how the machine learning model can predict the true negative in each category so, it measures the portion of the true negatives that are correctly identified by the machine learning model.

$$Specificity = \frac{TrueNegative}{TrueNegative + FalsePostive} \quad [7]$$

The model without any filters reached 0.9592 specificity, the model with low pass filter achieved 0.9434 specificity and the model with high pass filter reached 0.9876 specificity.

Table 1: shows validation results for the three models

Validation Technique	Model without a filter	Model with low pass filter	Model with high pass filter
Accuracy	0.9274	0.8942	0.9668
Precision	0.9469	0.9250	0.9843
Sensitivity	1.0	1.0	0.9968
Specificity	0.9592	0.9434	0.9876

Table 1 shows a summation for the results and the comparisons of the three models and approaches we tested.

As Table 1 shows there's no great variation regarding the sensitivity. The model with high pass filter had the best results, followed by the model without a filter, then the model with low pass filter.

Conclusion

To sum up, the models could achieve good results classifying and differentiating the BPD and the normal according to their MRI. Moreover, taking into consideration the previous results using high pass filter achieved the best results then the model without a filter and the model with low pass filter which had no significant difference in their results. However, in order to improve the results and reach more reliability we need more dataset as the main problem was the limited dataset.

It was highly recommended that the high pass filter achieved the best results because it makes the image more sharp so the machine learning model can understand and differentiate between the MRI images better which help the psychiatrists to diagnose and understand the origins of the BPD more and understand whether it's related to brain structure or not. The limitations of the study, is the small sample size and possibility of any biases in the dataset. In order to overcome these limitations, it's advised to test on larger datasets or exploring additional image processing techniques like try with bandpass filter and change the cut off frequencies of the filters used.

Data Availability Statement

The datasets generated and/or analysed during the current study are available in the [ds000214] repository, [https://github.com/OpenNeuroDatasets]

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