Journal of Scientific and Technical Research
15 (2) 2025, 52-61
www.publishingindia.com/jstr
https://doi.org/10.21863/jstr/2025.15.2.005

High-Pass-Filtering Impacts the Accuracy of the Hybrid Model for Detection of Brain State Allied with Isha Shoonya Meditation

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Abstract: ***Background:*** **Many psychological and physical health problems are instigated due to existence of stress because of chaotic lifestyle. It is a noteworthy hazardous factor for several cerebral disorders and hence, impacts the superiority of life. To manage the stress, it is important to practice the meditation and yoga. Electroencephalogram (EEG) is the chosen analytical tool in this research as it is economical, non-invasive and easy to operate. This study mainly focuses on Deep Learning (DL) technique for recognition of brain state linked with Isha Shoonya meditation. To obtain the best outcomes, the task was accomplished for identifying meditative brain state with varying High Pass Filter (HPF) frequencies.**

Purpose: **The performance of the model depends upon various factors like model designing, hyperparameter tuning, Independent Components Analysis (ICA), and HPF. This study emphasized on one important factor how the high pass filtering impacts the accuracy of the model. The filter setting was done to dissimilar frequencies: 0.1 Hz, 0.5 Hz, 1 Hz, and 2 Hz to investigate the varying impacts of HPF on the presented Hybrid model. The performance was systematically assessed by varying the filter settings.**

Methods: **Hybrid model was designed and examined how the high pass filtering impacts the accuracy of the model.**

Results and Conclusion: **Accuracy of 68.93% with filter setting at 0.1 Hz, 87.50% at 0.5 Hz, 96.41% at 1 Hz, and 93.76% at 2 Hz was attained. The maximum accuracy of 96.41% was achieved for Hybrid model at 1 Hz for Isha Shoonya meditation. HPF at 1 Hz gave decent outcomes.**

Keywords: Deep Learning (DL), Electroencephalogram (EEG), High Pass Filter (HPF), Hybrid model, Isha Shoonya meditation.

I. Introduction

Stress causes various psychological and health disease such as mood disorders, depression, anxiety, and aggressive behavior [1]. To decrease the stress level, the best alternate of medicinal treatment is meditation [2]. Practicing *Isha Shoonya* meditation helps to manage emotions, and enhance antidepressant effect and relaxation [1]. Meditation is also associated with metabolic and musculoskeletal benefits [3]. Mindfulness meditation exposed optimistic outcomes related to emotional stability and various medical disorders [4] and proved to be the best complementary medicine treatment [5]. As EEG signals are sensitive to meditation changes, so they may be the best approach for measure meditation ability [6]. EEG is the chosen analytical tool in this research as it is economical, non-invasive and easy to operate [7]. EEG analysis is a significant tool in neural engineering and neuroscience with its applications [8]. Scientific research work on meditation have powerfully increased in few years [9]. The recent curiosity in these olden mental techniques is associated with the advancement of new brain imaging skills which results in integration these practices, into clinical interventions and psychotherapeutic [9]. Many of the diagnostic tools used in EEG studies have used Machine Learning (ML) techniques to discover the related information for neuroimaging and neural classification [8]. In recent years, ML has significantly used from detection of epilepsy seizure to motor imagery and emotion recognition [10-17]. The advancement in ML led to use of DL techniques in the study of EEG signals. DL has gained an immense recognition in the field of research in recent years [18]. Among various DL approaches, Convolutional Neural network (CNN) is the most advanced algorithm. CNNs have made an innovative influence in the field of medical science, especially on medical imaging to solve complex problems [18-20]. The automatic classification is a vital stage towards making the use of EEG less dependent on trained specialists [8].

Zhang *et al.* [21] classified motor imagery signals using two neural networks: convolutional and wavelet**.** Shamsaldin *et al.* [22] provided the facts of the application of CNNs in following fields, natural language processing and computer vision, and determined that CNN offers improved outcomes. A. Rafiei *et al*. [23] obtained an accuracy of 91.67% for all channels and

87.5% after selecting the channels for identification of Major Depressive Disorder.

R. M. Vivot *et al.* [24] performed an experiment on, 27 meditators, each of Himalaya and *Isha Shoonya*, 30 controls, and 20 Vipassana meditators. They extracted Sampling Entropy and classification was done with Random Forest and proved that with long time practice, high entropy states can be attained.

Chaudhary *et al.* [25] extracted Power Spectral Density (PSD) and more than 70% average accuracy was attained. Craik *et al.* [8] have made a systematic review on DL applications like classification tasks, impact of input designs on training and DL architectures on various tasks.

The description of methods used, procedures and outcomes described by the authors is given in Table I.

Table I: Description of Methods Used and Outcomes Achieved

Sr. No.	*Description*	*Type*	*Method*	*Conclusion*	*Year*
1.	Lin and Li [26]	Identified meditation mind state	Feature Extraction-Sample and Approximate Entropy Classification- Gaussian Mixture Model (GMM) Tree Bagging, SVM	1. Tree bagging provided the lowest misclassification rates. 2. With increase in time length, the misclassification rates decreased for Sample Entropy. 3. By discretizing EEG data, classification outcomes enhanced.	2017
2.	Oh *et al.* [27]	Participants- 20 Parkinson's disease and 20 normal. Identified Parkinson's disease	Designed a deep CNN model (13 layers)	84.71% sensitivity, 88.25% accuracy, and 91.77% specificity	2018
3.	Sharma *et al.* [1]	Participants- 25 non-meditators and 25 meditators	Feature extraction using Discrete Wavelet Transform Classification- Multilayer Perceptron Neural Network	87.2% accuracy, 87.1% sensitivity, and 87.4% specificity	2019
3	Shamsaldin *et al.* [22]	Review study of CNN applications	Natural Language Processing, Computer Vision	CNN presented improved accuracy in comparison to other approaches.	2019
4	Kora *et al.* [3]	Comparative review study	----	----	2021
5	Rashed-Al-Mahfuz *et al.* [13]	Data availability- Bonn University, five sets (A-E) Detected seizures	Continuous Wavelet Transform (CWT) and STFT Classification- VGG16 and ResNet50 (FT-Method 3) VGG16 and ResNet50 (TL-Method 2), Shallow model based on CNN architecture (Method 1),	FT-VGG16- 99.21% (Maximum highest accuracy)	2021
6	Chaudhary *et al.* [25]	Various styles of meditation	PSD Classifier-Neural Network, ML	Average classification accuracy- above 70%	2022

Sr. No.	*Description*	*Type*	*Method*	*Conclusion*	*Year*
7	Munjal and Varshney [28]	19 *Vipassana* meditators, 31 controls, and 24 *Himalayan Yoga* meditators.	Inception Convolutional Recurrent Neural Network (IC-RNN) and CNN	86.19% maximun accuracy for IC-RNN, 99.45% maximum accuracy for CNN at 1Hz (for *Vipassana* meditation), 88.15% maximum accuracy for IC-RNN and 100% for CNN at 1Hz (for the *Himalayan Yoga* meditation) HPF at 1 Hz offered good performance	2025

II. Data Preprocessing

The experiment has conducted on open-access data that consists of 31 controls and 20 *Isha Shoonya* [29]. 64 channels Biosemi EEG acquisition system was used to collect the data at the Meditation Research Institute (MRI) in Rishikesh, India [9].

The explanation of procedure for collection of data and approaches is specified in the paper [9]. *Isha Shoonya* meditators group had a decent practice of tradition specific meditation. Control subjects did not have the meditation practice experience and were given instructions to concentrate on exhale and inhale. Subject 79 to 98 belongs to *Isha Soonya* group and 25 to 55 belongs to control group. This study emphasized on one important factor how the high pass filtering impacts the accuracy of the model. Fig. 1 shows the flow chart of identification of brain state process. The electrodes' positioning is shown in Fig. 2. The signals were down sampled at 200 Hz. A band pass filter of 1-45 Hz was used and artifacts were removed by Independent Components Analysis (ICA). ICA component score of subject 48 of control group is shown in Fig. 3 and subject 87 of *Isha Shoonya* meditator group is shown in Fig. 4.

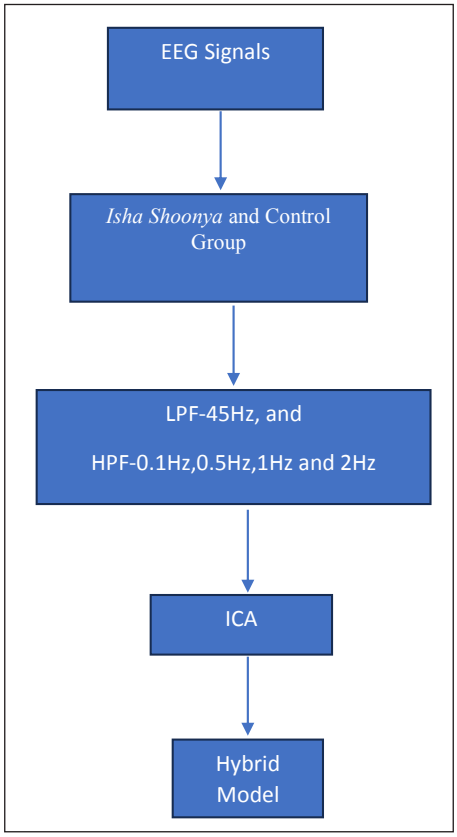

Fig. 1: Flowchart for Classification of EEG Signals

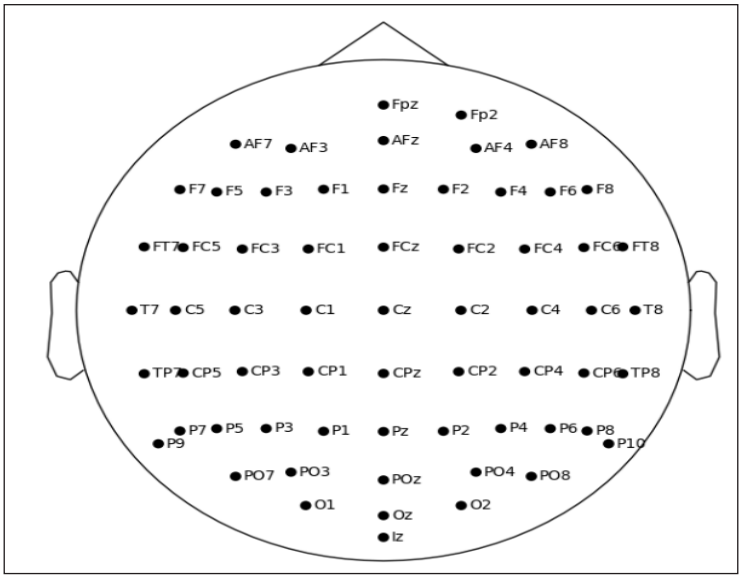

Fig. 2: Electrode Positions Using 'Biosemi64'

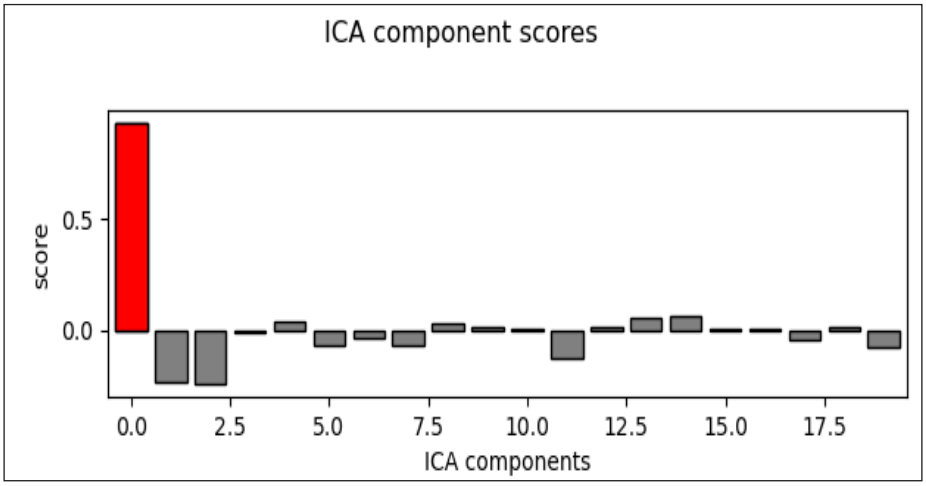

Fig. 3: ICA Components Score of Subject 48 of Control Group

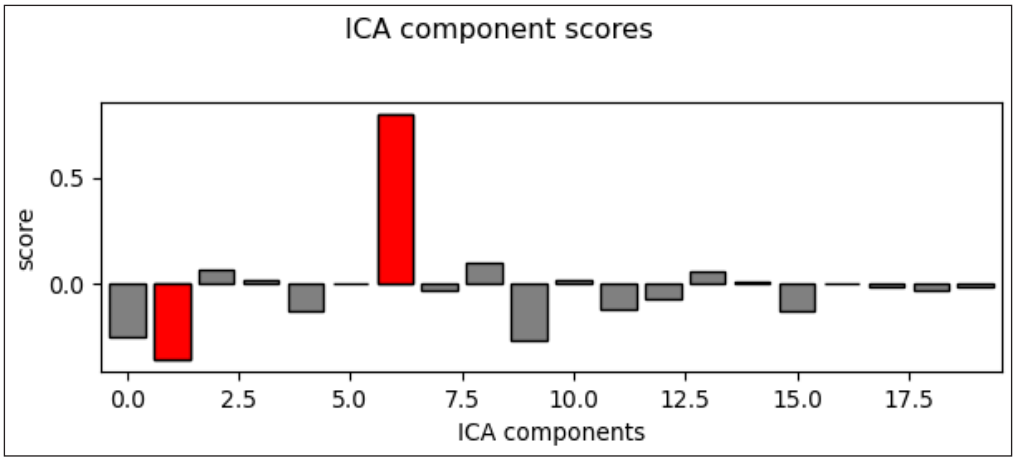

Fig. 4: ICA components Score of Subject 87 of *Isha Shoonya* Meditation Group

III. Hybrid Model

The concatenation of three convolutional layers is completed in order to make the four inception blocks [30] [31]. All the blocks are serially connected and trailed by four Gated Recurrent Unit (GRU) layers [31]. The last is the dense layer. The stride is set at 2 for all the convolutional layers. The filter size is set at 2 for layers 1,5,9, and 13. The filter size is set at 4 for layers 2,6,10, and 14. The filter size is set at 8 for layers 3,7,11, and 15. The parameters of Hybrid model are summarized in Table II. Fig. 5 shows the plotted Hybrid model.

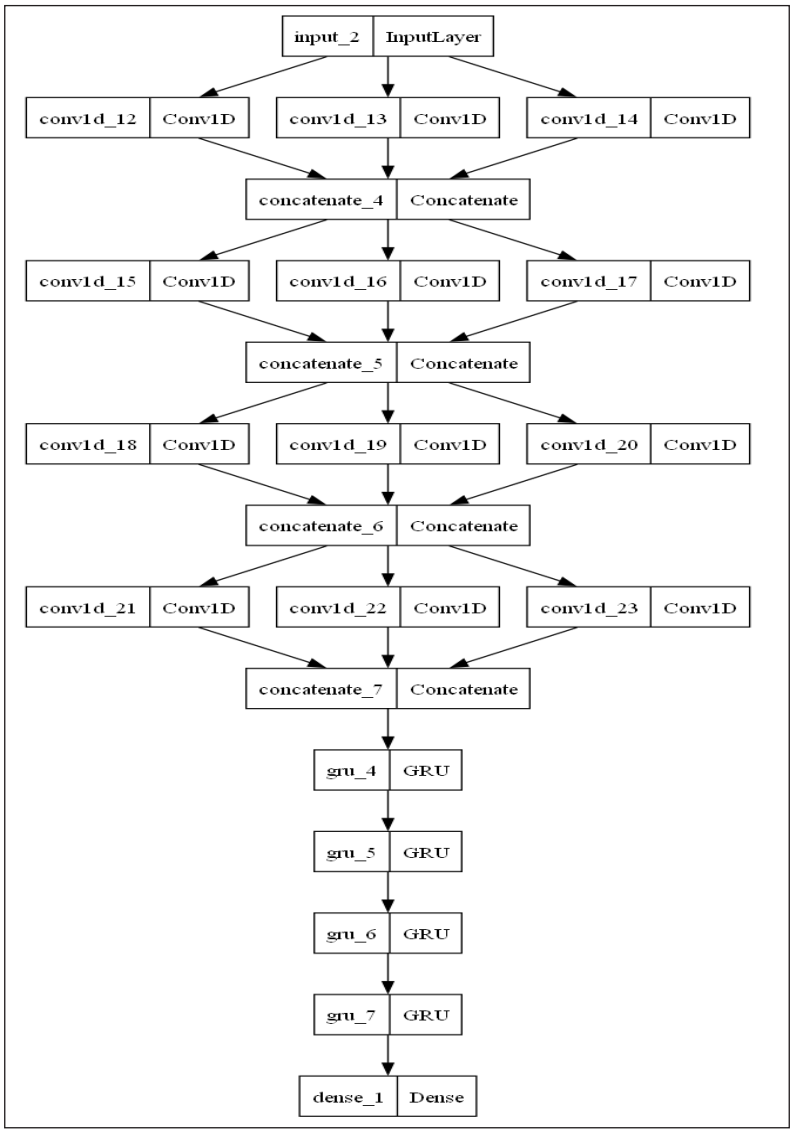

Fig. 5: Hybrid Model

Table II: Parameters of Hybrid Model

Layer	*Filter Size*	*Stride*	*Output Shape*
1 (conv1d_12)	2	2	1401,16
2 (conv1d_13)	4	2	1401,16
3 (conv1d_14)	8	2	1401,16
4 (concatenate_4)	-	-	1401,48
5 (conv1d_15)	2	2	701,16
6 (conv1d_16)	4	2	701,16
7 (conv1d_17)	8	2	701,16
8 (concatenate_5)	-	-	701,48
9 (conv1d_18)	2	2	351,16
10 (conv1d_19)	4	2	351,16
11 (conv1d_20)	8	2	351,16

Layer	*Filter Size*	*Stride*	*Output Shape*
12 (concatenate_6)	-	-	351,48
13 (conv1d_21)	2	2	176,16
14 (conv1d_22)	4	2	176,16
15 (conv1d_23)	8	2	176,16
16 (concatenate_7)	-	-	176,48
17 (gru_4)	-	-	176,16
18 (gru_5)	-	-	176,16
19 (gru_6)	-	-	176,16
20 (gru_7)	-	-	16
21 (dense)	-	-	1

IV. Results and Discussion

Table I shows the comparison of outcomes at different filters for classification task. Accuracy of 68.93%, sensitivity of 57.41%, and specificity of 80.38% was attained with filter setting at 0.1 Hz. Accuracy of 87.50%, sensitivity of 81.77%, and specificity of 91.12% was attained with filter setting at 0.5 Hz. Accuracy of 96.41%, sensitivity of 97.66%, and specificity of 95.68% was attained with filter frequency at 1 Hz. Accuracy of 93.76%, sensitivity of 87.70%, and specificity of 97.99% was attained with filter frequency at 2 Hz. The maximum accuracy of 96.41% was achieved for Hybrid model at 1 Hz filter setting for *Isha Shoonya* meditation identification. Accuracy versus epochs plots with various filter frequencies are shown in Fig. 6 to Fig. 9. The confusion matrices with various filter frequencies are shown in Fig. 10 to Fig. 13.

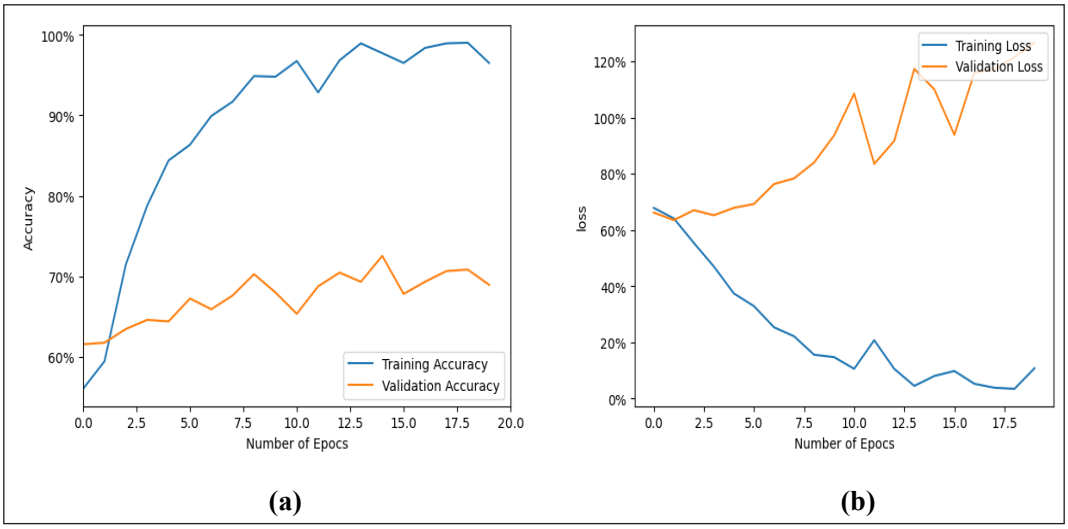

Fig. 6: (a) Accuracy (in %age) Versus Number of Epochs Plot; (b) Loss (in %age) Versus Number of Epochs Plot for HPF-0.1 Hz

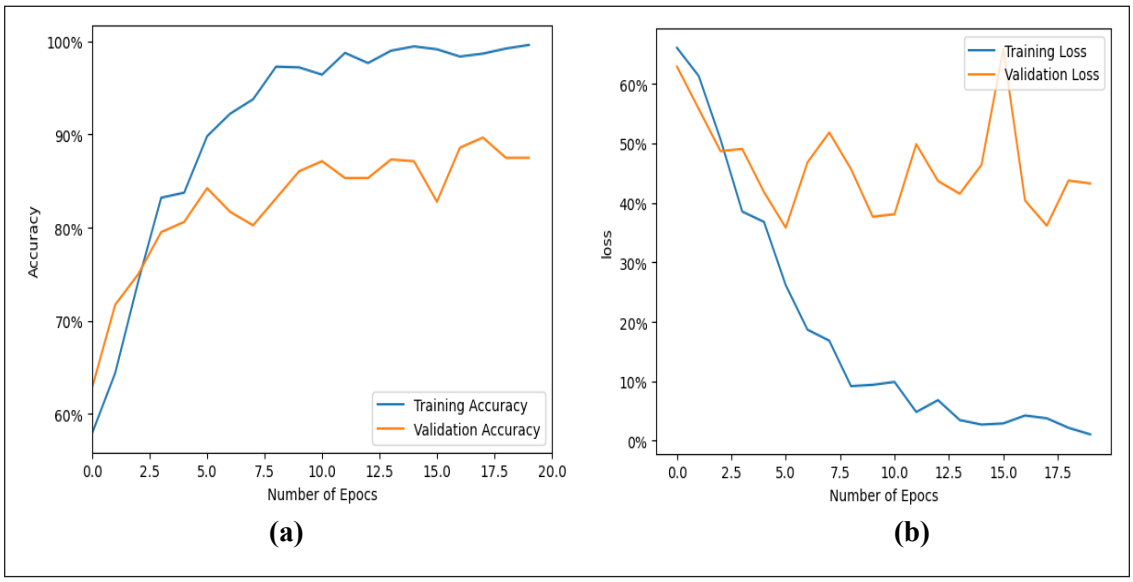

Fig. 7: (a) Accuracy (in %age) Versus Number of Epochs Plot; (b) Loss (in %age) Versus number of Epochs Plot for HPF-0.5 Hz

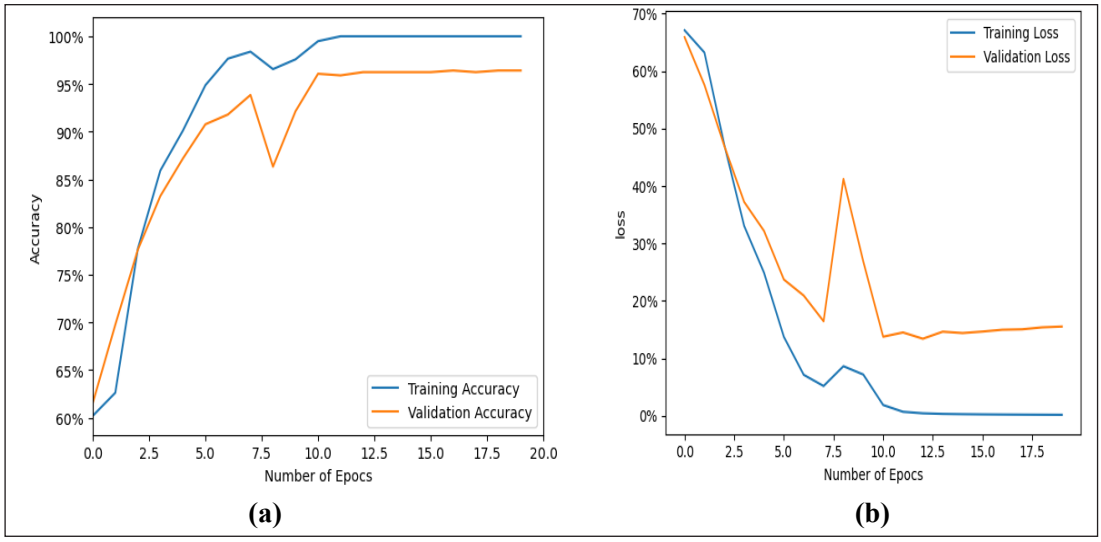

Fig. 8: (a) Accuracy (in %age) Versus Number of Epochs Plot; (b) Loss (in %age) Versus Number of Epochs Plot for HPF-1 Hz

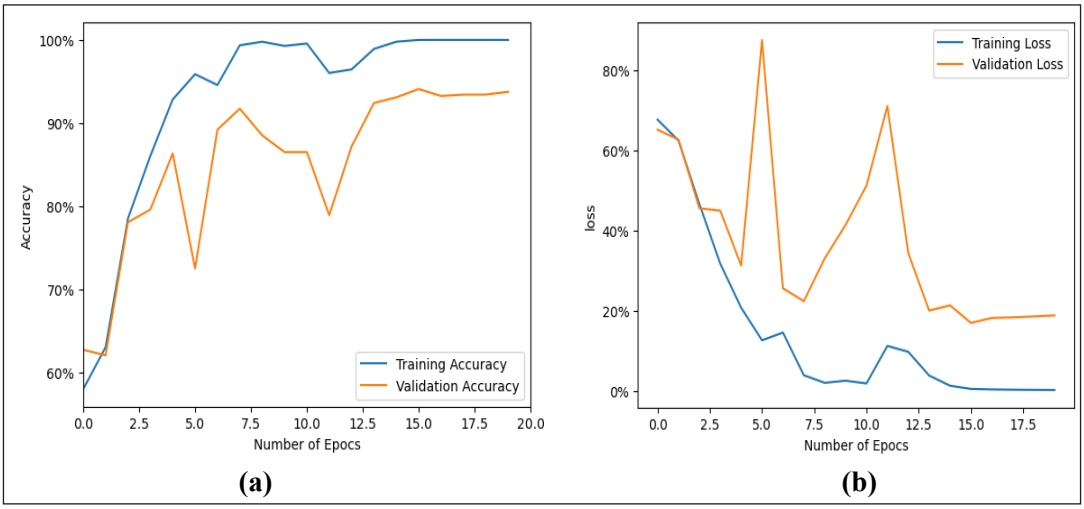

Fig. 9: (a) Accuracy (in %age) Versus Number Of Epochs Plot; (b) Loss (in %age) Versus Number of Epochs Plot for HPF-2 Hz

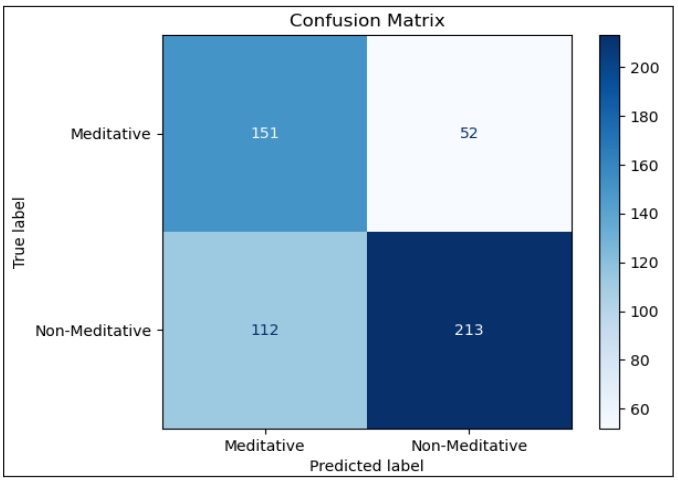

Fig. 10: Confusion Matrix with HPF-0.1 Hz

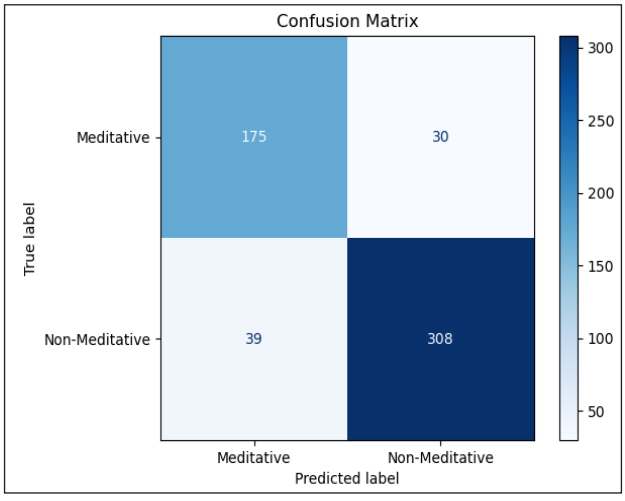

Fig. 11: Confusion Matrix with HPF-0.5 Hz

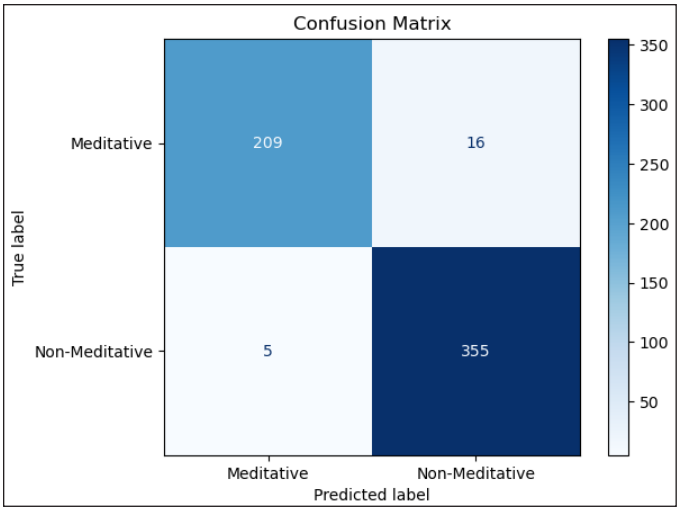

Fig. 12: Confusion Matrix with HPF-1 Hz

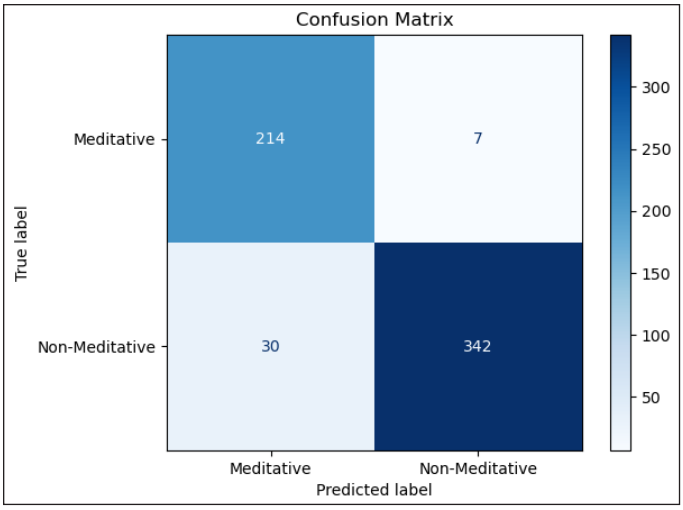

Fig. 13: Confusion Matrix with HPF-2 Hz

TABLE III: CLASSIFICATION RESULTS WITH DIFFERENT HPF SETTINGS

HPF (Hz)	*True Positive*	*True Negative*	*False Positive*	*False Negative*	*Accuracy*	*Sensitivity*	*Specificity*
0.1	151	213	52	112	68.93%	57.41%	80.38%
0.5	175	308	30	39	87.50%	81.77%	91.12%
1	209	355	16	5	96.41%	97.66%	95.68%
2	214	342	7	30	93.76%	87.70%	97.99%

V. CONCLUSION

The high pass filtering is an important preprocessing stage to increase the performance of the model. We thus assessed how the high pass filtering in preprocessing step impacts the performance. For this, hybrid model was designed to investigate the varying impacts of HPF. The filter setting was done to dissimilar frequencies: 0.1 Hz, 0.5 Hz, 1 Hz, and 2 Hz.

The key objective was to recognize the mind state associated with *Isha Shoonya* meditation. The task was performed with varying HPF frequencies to attain the best outcomes. Hybrid model was designed and compared the results for various HPF frequencies. Accuracy of 68.93% with filter setting at 0.1 Hz, 87.50% at 0.5 Hz, 96.41% at 1 Hz, and 93.76% at 2 Hz was attained. The maximum accuracy of 96.41% was achieved for Hybrid model with filter setting at 1 Hz for the *Isha Shoonya* meditation classification. HPF at 1 Hz gave decent outcomes.

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