Intelligent Automation
& Soft Computing

Tech Science Press

DOI: 10.32604/iasc.2024.041535

ARTICLE

A Robust Method of Bipolar Mental Illness Detection from Facial Micro Expressions Using Machine Learning Methods

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Received: 26 April 2023 Accepted: 12 January 2024 Published: 29 March 2024

ABSTRACT

Bipolar disorder is a serious mental condition that may be caused by any kind of stress or emotional upset experienced by the patient. It affects a large percentage of people globally, who fluctuate between depression and mania, or vice versa. A pleasant or unpleasant mood is more than a reflection of a state of mind. Normally, it is a difficult task to analyze through physical examination due to a large patient-psychiatrist ratio, so automated procedures are the best options to diagnose and verify the severity of bipolar. In this research work, facial micro-expressions have been used for bipolar detection using the proposed Convolutional Neural Network (CNN)-based model. Facial Action Coding System (FACS) is used to extract micro-expressions called Action Units (AUs) connected with sad, happy, and angry emotions. Experiments have been conducted on a dataset collected from Bahawal Victoria Hospital, Bahawalpur, Pakistan, Using the Patient Health Questionnaire-15 (PHQ-15) to infer a patient's mental state. The experimental results showed a validation accuracy of 98.99% for the proposed CNN model while classification through extracted features Using Support Vector Machines (SVM), K-Nearest Neighbour (KNN), and Decision Tree (DT) obtained 99.9%, 98.7%, and 98.9% accuracy, respectively. Overall, the outcomes demonstrated the stated method's superiority over the current best practices.

KEYWORDS

Bipolar mental illness detection; facial micro-expressions; facial landmarked images

1 Introduction

Mental illness, impacting millions globally, poses a significant public health challenge, with early detection and treatment crucial for improving the health and well-being of those affected. The human face plays a pivotal role in emotion interpretation, leading to demographic estimation through facial image analysis for diverse applications, including forensics and social media. Psychologists rely on facial expressions to gauge mental states, although the vast range of expressions complicates concrete assessments. In this context, facial activity units become vital in diagnosing psychological disorders.

Bipolar disorder (BD), identified by the World Health Organization as a leading cause of disability and reduced life expectancy among youth, often gets misdiagnosed as major depressive disorder. This complicates treatment, despite being a prevalent condition. BD, characterized by mood swings from high (mania or hypomania) to low (depression), affects various aspects of life and can vary in frequency and duration. Treatment includes medications and psychotherapy, but symptoms and severity vary widely. Factors like family history, personal stressors, and life events can trigger BD, emphasizing the need for accurate diagnosis methods, where machine learning offers promising advancements.

BD can be diagnosed using both clinical and non-clinical diagnostic methods. Patient reports or clinical decisions made in light of the Diagnostic and Statistical Manual of Mental Disorders (DSM) constitute the sole basis of the symptom severity-based clinical method, which is computerized of Patient Health Questionnaire-15 (PHQ-15) in (DSM-5) [1]. Clinical methods used for bipolar detection are mainly consisting of two screening test, i.e., Mood Disorders Questionnaire (MDQ) and Hypomania Checklist (HCL-32) [2].

Facial micro-expressions indicative of the degree and kind of bipolar disorder can be recognized by computer vision. When these methods are combined, it is possible to create computer-aided diagnostic systems that can be used to screen the entire population without any hesitancy or other barriers. Both the patient and the psychiatrist may benefit financially and timewise from the use of such technologies. In addition, confidentiality can be maintained, which is essential given the social stigma. So, these technologies have the potential to be efficient, dependable, secure, non-invasive, real-time, resilient, and helpful for early-stage detection.

Facial micro-expression refers to the almost imperceptible but telling changes in facial muscle activity that can reveal whether a person is trying to conceal their true emotions or even their mental state. Therefore, micro-expression recognition attracts rising study efforts in both domains of psychology and computer vision [3]. Every suspect, no matter how innocent-looking on the outside, will show some sort of reaction under questioning, even if it is just a short-term micro-expression [4]. The suspect’s expression negates her words.

The main contribution of this research is key fold into the following. This research examined the effectiveness of applying Convolutional Neural Network (CNN). Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Decision Tree (DT) to diagnose bipolar illness. The suggested CNN-based and other CNN-based pretrained models are used to classify noisy and aligned images in the first module, while in the second module, SVM, KNN, and DT are utilized to classify the extracted features.

The paper is organized as follows: Section 2 contains a review of related studies, while Section 3 embodies details about the data acquisition, preprocessing, and the proposed CNN model for bipolar detection. In Section 4, experimental work is performed; this section also represents experimental results, their discussions, and comparison with the state-of-the-art methods. Section 5 concludes the conducted research work and future directions of this conducted study.

2 Literature Review

Several investigators proposed several diagnostic models using automated techniques to detect BD in non-invasive manners.

In this study [5], the dataset used for the experiments was behavioral simulations of bipolar patients experiencing mixed episodes. The study’s computational component used Matlab scripts based on Euler’s mechanism. The proposed system takes in all the probability data for an event while keeping the noise value constant at 0.1. The study also determines that an amplitude of 0.01 is the maximum for a customarily distributed event. The practical utility of the proposed model is significantly high for real-world cases of bipolar disorder. In this study [6], two datasets used in this study BD Corpus [7] and the Well-being dataset. The Proposed model audio-visual Long-Short-Term Memory (LSTM), audio-visual-textual LSTM & adaptive nonlinear judge classifier was used to classify BD and Depression on both datasets. Achieved results Using audio-visual-textual LSTM from BD corpus's as per accuracy = 91.6%, and audio-visual LSTM from Well-being dataset's as per F1 = 0.870. This study improved by adding different samples (audio, visual and textual) of the same patients. In this study, multiple video recordings of the same patient were used, so there is a need to add more patients and a variety of videos from different patients.

In this study [8], BD and borderline personality disorder (BPD) happen together; it is hard to tell them apart from each disorder. The study aims to use machine learning (ML) to tell BP/BPD apart from BP and BPD on their own. Diagnoses from the DSM were given to the participants, and self-report measures looked at personality, ways to control emotions, and how parents were seen when they were young. BP was given to 82 participants, BPD to 52, and BP and BPD to 53. The accuracy of ML-based diagnoses for BP/BPD *vs.* BP was 79.6%, and for BP/BPD *vs.* BPD, it was 61.7%. Limited dataset used in this study.

In this study [9], dataset participants met the inclusion criteria and sought treatment at the Bipolar Outpatient Clinic in the Medical Faculty at Eskisehir Osman Gaze University, Turkey. The neurocognitive evaluation was conducted using six tests from the CANTAB test battery, and participants were placed into appropriate categories using the Polyhedral Conic Functions algorithm. An accuracy of 78.0% was achieved in distinguishing bipolar patients from healthy controls. In another paper [10], major depressive and bipolar disorder have been detected Using a machine learning predictive model. This study achieved results as per Area under the Curve (AUC) = 0.97, accuracy on Major Depressive Disorder (MDD) = 92.0% and accuracy of BD = 86.0%. Patients were recruited from a single center and ethnic group, limiting generalizability.

In this study [11], the benchmark dataset Turkish Audio-Visual Bipolar Disorder Corpus (AVEC) is used to classify the BD state. CNN is used for the classification of facial features from video recordings. Long-Short-Term Memory (LSTM) is used to classify extracted features from facial images and achieved results from the proposed model as per Unweighted Average Recall (UAR) of 60.6%. In this study [12], BD patients are classified Using an audio-visual dataset from AVEC-2018. A Fisher Vector encoding of ComParE's low-level descriptors (LLDs) used for screening for bipolar disorder. The best test set result achieved UAR = 57.4%. This study needs to improve results in terms of accuracy.

In this study [13], the IncepLSTM framework was used to categorize BD severity. IncepLSTM uses a CNN with filters of varying kernel sizes and LSTM on the feature sequence to effectively model multi-scale temporal audio clues. This experimental work made use of the AVEC-2018 dataset. An accuracy of 65.0% was achieved Using IncepLSTM in this study. This study needs to improve results in terms of accuracy.

It is evident that each study contributes uniquely through diverse methodologies, such as computational modeling, audio-visual-textual LSTM, and machine learning diagnostics, with varied datasets ranging from behavioral simulations to the Turkish Audio-Visual Bipolar Disorder Corpus. While these studies collectively advance the understanding and diagnosis of bipolar disorder, often-achieving high accuracy and innovative classification methods, they also reveal limitations like limited generalizability and varied success rates across different modalities. This highlights the need for more comprehensive and diverse approaches in future research to address these gaps and continue advancing the field.

3 Material and Methods

The proposed method of bipolar disorder detection based on facial images consists of several steps as follows.

3.1 Dataset Acquisition

The dataset has been collected from the Department of Psychiatry at Bahawal Victoria Hospital in Bahawalpur, Pakistan. It comprises 1–5-min videos of each bipolar patient and healthy controls. When conducting PHQ-15 interviews, all patients signed a consent form and gave their informed consent to be videotaped. According to a clinical trial conducted by a team of psychiatrists, there were 310 bipolar patients and 192 healthy controls. While acquiring the videos, interviews were conducted using a questionnaire prepared following the PHQ-15 and DSM-V. Table 1 displays information about the patients and healthy controls used for research and experiments for at least two hours before the examination.

Table 1: Details of the dataset used for research and experiments

Patient/health	No. of patients	Gender	Age group	Marital status	Job occupation
Patients	45	Male	19–21	Unmarried	Farmer
	60		50–60	Married	Job holder
	50		41–50		
	55		51–60		
	46	Female	21–30		Housewife
	54		31–40		Job holder
Healthy	45	Male	41–64	Married	
	62		31–40		Businessman
	50		21–30	Unmarried	Job holder
	35	Female	21–30		

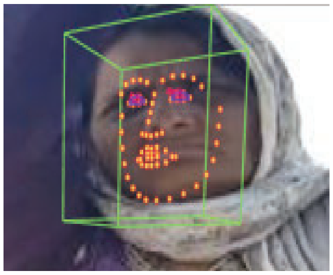
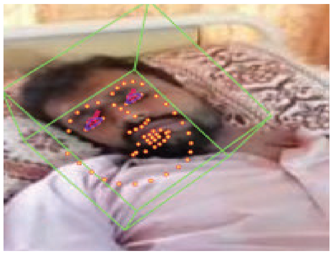
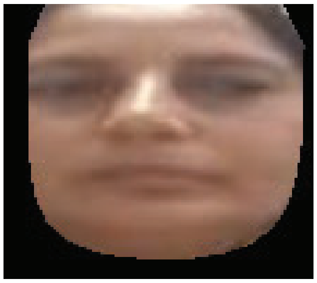
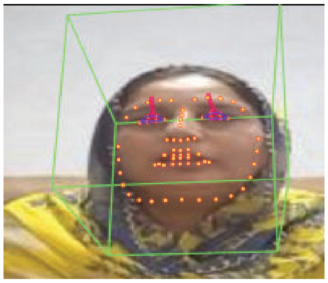
3.2 Preprocessing

The videos were turned into frames that were each 256 $*$ 256 pixels. Every video lasts one to five minutes and has 24 frames per second. There are 5.25 million bipolar images and 3.25 million healthy person images that were taken from videos. So, a lighter version of this dataset was made by only including one frame from every two frames that came before it. Due to the fleeting and subtle nature of microexpressions, the possibility of losing them increases as more frames are missed. This explains why the volume cannot be decreased by dropping further frames.

3.3 Features Extraction

The OpenFace tool [14] was used to obtain noise-free data for aligned faces, 2D landmarking, and Action Unit (AUs) [15] detection & estimation. AUs [16] are based on micro expressions during sadness, fear, disgust, contempt, and anger. Table 2 shows examples of aligned faces, which are saved as 256256 JPEG files. Face landmarks, like the mouth, ears, and eyes, are used to crop and line up each frame. Four features, including AUs, gaze, pose, and landmarks, were found and saved in a features file (in CSV format) so that they could be used in future experiments to figure out how they can be used to tell BD patients from healthy controls.

Table 2: Original/noisy images, aligned and landmarked faces

Id	Condition	Original/noisy images	Aligned face	Landmark face
1	Bipolar			
2	Bipolar			
3	Normal			

3.4 The Proposed CNN Architecture

CNN helps solve any machine vision-related problem. The image is analyzed and mapped into a more manageable format for improved prediction, with no critical details lost. The two main components of CNN are convolution and pooling. As a layer dedicated to extracting features that help to preserve spatial information, convolution does an excellent job of doing just that. To optimize the application, the pooling layer reduces the size of the significant characteristics. Next, an activation function containing a fully connected layer receives the simplified features.

3.4.1 Convolutional Layer

The kernel or filter is the vital part of the convolutional layer that does the work. This part multiplies the input data by the two-dimensional array of weights for a two-dimensional image. The convolutional layer oversees obtaining low-level features such as edges, color, and gradient orientation. More layers are added to obtain high-level features, including micro-expressions that can quickly identify the severity of bipolar disorder. Eq. (1) depicts the convolutional process.

$$conv(I,K)_{x,y} = \sum_{i=1}^{n_h} \sum_{j=1}^{n_w} \sum_{k=1}^{n_c} K_{i,j,k} I_{x+i-1,y+j-1,k} \tag{1}$$

where I = image, K = filter/kernel, x = x-coordinate, y = y-coordinate, n_h = height of image, n_w = Width of the image, and n_c = the number of channels.

3.4.2 Pooling Layer

In this layer, we minimize the sizes by which the convolved features are represented to control the amount of computing power required to process the enormous dataset. Additionally, it is required to separate the primary features that are not affected by changes in position or rotation. This aids in efficient model processing. Mainly, two distinct forms of pooling operations exist, i.e., maximum pooling and average pooling. In max-pooling, the maximum value from the image portion covered by the kernel is returned, while in average-pooling, the average of all numbers from the image portion covered by the kernel is provided. Max-pooling outperforms average-pooling in the facial dataset when processed to extract micro-expressions, which was incorporated into the proposed design.

3.4.3 Rectified Linear Unit (RELU) Layer

The activation function converts the data from linear to nonlinear, essential for solving complex problems. Standard activation functions include Softmax, Exponential Linear Unit (ELU), sigmoid, and RELU. During the proposed CNN model's feature extraction, the RELU function increases nonlinearity to learn about complex relationships in the data. It can minimize the interaction effects as it returns 0 for negative values. This function is linear and nonlinear for two halves of the input data. It is primarily implemented in the hidden layer due to the formation of dead neurons. RELU function is computationally efficient because it has zero derivatives for negative numbers and 1 for positive numbers; due to this, some of the neurons get activated. Its function is shown in Eq. (2).

$$f(x) = max(0, x) \tag{2}$$

The f(x) function returns a maximum value between 0 and x.

3.4.4 Softmax Function

It is a nonlinear feed-forward activation function defined for actual input values. It has a value between 0 and 1. It is a smoothing function that is useful for derivation and classification. To calculate gradients in the neural network, derivation is required. Calculating the optimal parameters for neural network learning Using the constant derivative is impossible. It is not centered and has a vanishing gradient problem. As a result, learning is limited and time-consuming. It is mainly used in the output layer and works best for binary classification. Eq. (3) depicts the sigmoid function. This function was used to classify bipolar in the proposed CNN architecture.

$$S(x) = \frac{1}{1+e^{-x}} \tag{3}$$

The sigmoid function S(x) takes any real number x and returns a value between 0 and 1.

3.4.5 Fully Connected Layer

The pooled feature map is flattened before applying a fully connected layer. The proceeds data through hidden layers are flattened into a suitable column vector and fed to the fully connected layer. Then back-propagation is applied to each iteration of training. The fully connected layer is responsible for learning a nonlinear combination of high-level features. A fully connected layer has all its connections with the activation units of the layers that came before it. Using the Softmax classification method, the model can tell over time which features are dominant and which are not. It gives the feature map vectors for each category values between 0 and makes them the same. Normalization is done to obtain a means close to zero that accelerates the learning process and is a prime factor for faster convergence. Convergence is when CNN has reached a constant learning rate and does not improve further.

3.5 Hyper Parameters of the Proposed CNN Architecture

3.5.1 Dropout

This CNN architecture hypermeter is used to prevent over-fitting. This improves the model's efficiency and generalizability. It has a value between 0.0 and 0.9. For network weight thinning, nodes are temporarily removed from the CNN along with all their incoming and outgoing connections based on the fixed probability value given. The proposed CNN model became overfitted when the dropout value was set to zero (0). Similarly, when it was set to 9, no learning resulted. Therefore, the proposed CNN architecture has an empirically determined value of 0.5.

3.5.2 Batch Size

Batch size is a gradient descent hypermeter that refers to the number of samples in the forward and backward pass before evaluating the internal model limitations. The batch size could be 32, 64, 128, 256, 512, etc. Since there are many frames to train the model, training time reached unaffordable limits when the batch size was set to 32. Therefore, the batch size in the proposed CNN architecture is set to 128 as a moderate value.

3.5.3 Momentum

Momentum is used to overcome the noisy gradient or bounce the gradient by accelerating the search movement in a direction to create inertia (constant movement). Descent momentum is used to optimize the gradient's performance. It generally reduces error and improves the learning algorithm's performance. It prevents optimization process hedging. It assists CNN in breaking out local minima so that a global minimum can be found. Most momentum values are close to one, such as 0.9 or 0.99. The proposed CNN architecture has an empirically determined momentum value of 0.9.

3.5.4 Learning Rate

The learning rate is augmented or diminished concerning the error gradient by adjusting the neural network's weights. It is the most critical gradient descent hypermeter and is responsible for stable and smooth training. The learning rate, accuracy, and time required to train the model are all factors to consider. The learning rate ranges from 0.0 to 1.0. In the proposed CNN architecture, the learning rate is set to 0.001.

Fig. 1 represents the architecture of the proposed CNN model. Table 3 represent the summary of the proposed CNN architecture. An overview of the proposed study is demonstrated in Fig. 2.

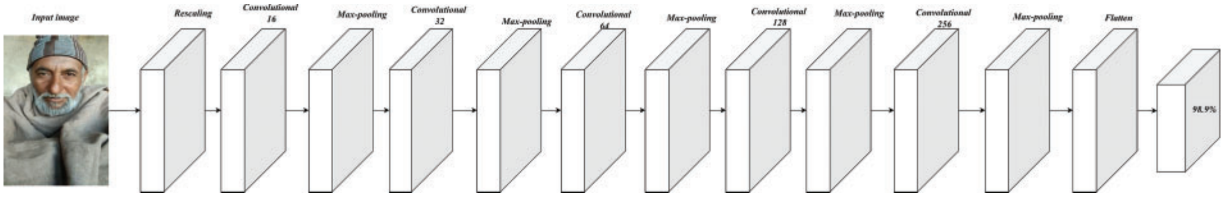


Figure 1: The proposed CNN architecture for bipolar detection

Table 3: Summary of the proposed CNN architecture for bipolar detection

Sr.	Layer	Size	Number of filters	Parameters
1	InputLayer	256, 256	3	0
2	Rescaling	256, 256	3	0
3	Conv2D	254, 254	16	448
4	MaxPooling2D	127, 127	16	0
5	Conv2D	125, 125	32	4640
6	MaxPooling2D	62, 62	32	0
7	Conv2D	60, 60	64	18496
8	MaxPooling2D	30, 30	64	0
9	Conv2D	28, 28	128	73856
10	MaxPooling2D	14, 14	128	0
11	Conv2D	12, 12	256	295168
12	MaxPooling2D	6, 6	6, 6	0
13	Flatten	9216		0
14	Dense	256		2359552
15	Dense	1		257
Total learnable parameters				2,752,417

4 Results and Discussions

So that system could get subsamples from the video, frames were taken so that one frame out of every two consecutive frames was discarded. So, the dataset of 502 controls produced 8, 50,440 data frames, of which 5, 25,000 belonged to bipolar, while 3,25,440 belonged to healthy controls. Due to the fleeting and subtle nature of micro-expressions, it was a risk of losing them if more frames were dropped. This explains why additional frames were not dropped. Initially, the experiments for bipolar detection from the noisy frames were done using pre-trained state-of-the-art CNN-based models, i.e., Rest-net 18, Squeeze-net, and Alex-net, and the proposed CNN-based model. However, the model was overturned because of the noise present in the frames. Then, to eliminate the noise, these frames are added to the OpenFace tool for aligned faces, 2D landmarks, and AUs and to extract features, including gaze, pose, and landmarks. The proposed and these pre-trained CNN-based model were applied to aligned faces to detect BD and healthy control. SVM, KNN, and DT were also used to classify AUs, gaze, pose, and landmarks features. These features were also combined and used to classify Using SVM, KNN and DT to detect BD and healthy control.

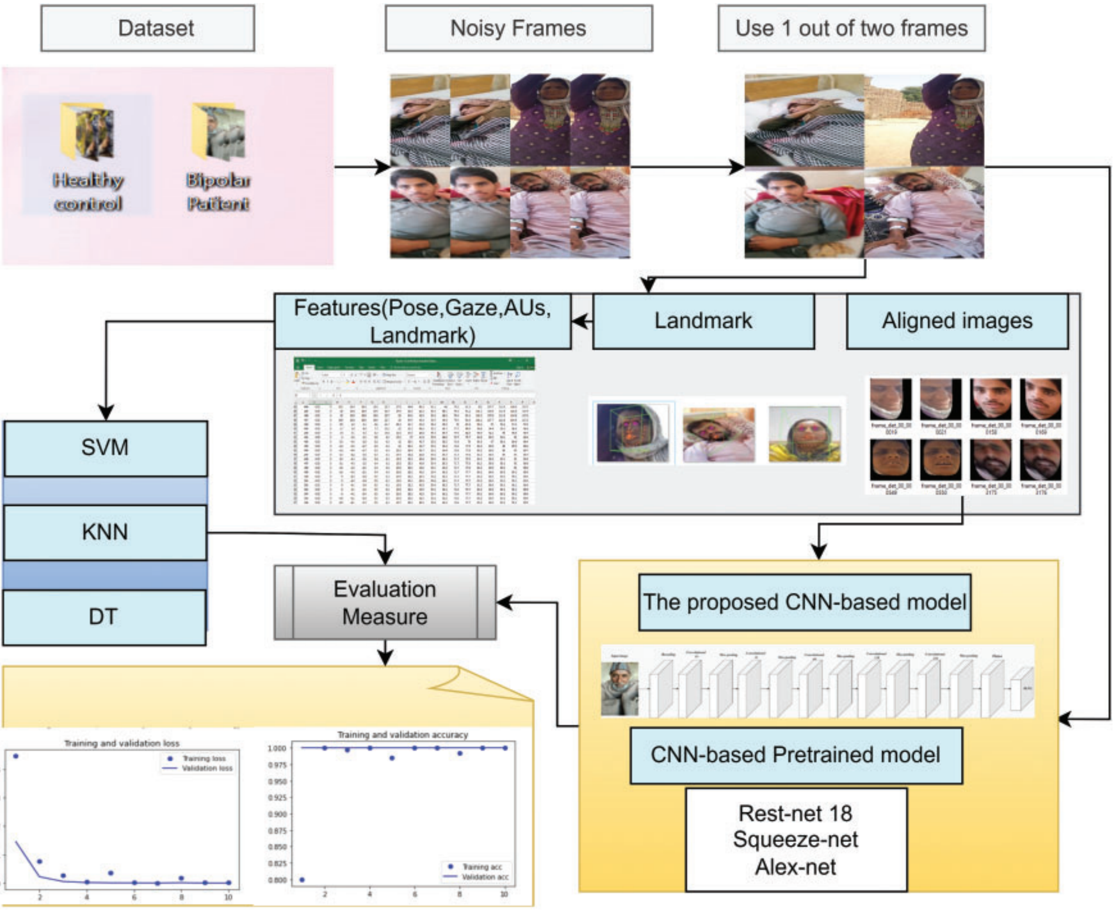


Figure 2: Overview of the proposed methodology

4.1 Results

70% of the dataset is used for training, 20% for testing, and the rest for 10% for validation. The results of all experiments are shown in Table 4. It is evident from Table 4 that only six pose features have obtained 95.4% validation accuracy when extracted from aligned images. Similarly, gaze features, 288 in number, gained lower classification rates. When only AUs features were extracted, it obtained 90.0% validation accuracy, which is reasonable. Fe features have an excellent classification rate, i.e., 99.9%, 98.7%, and 98.9% for accuracy archived against different classifiers, i.e., SVM, KKN and DT, respectively. To verify whether all these features collectively improve accuracy, these were combined, which achieved a remarkable classification rate of 99.9%, which is the maximum it can be Using SVM. All about SVM seems good; however, feature engineering is required. Therefore, aligned images are also classified Using CNN-based models, which do not need features to extract explicitly. When aligned, facial images were classified through Rest-net 18, Squeeze-net, and Alex-net obtained 98.0%, 97.0%, and 96.0% validation accuracy, respectively. This is also reasonable. However, all these pre-trained models have a large volume of learnable (parameters), significantly increasing the training time of a respective model. However, the proposed model consumes only 15 layers with 2,752,417 parameters. Therefore, it could be considered light-weight and requires less training time, achieving 98.9% validation accuracy. The accuracy obtained through the proposed CNN model is significantly higher than the pre-trained model. Therefore, it is more favorable for real-time bipolar detection from facial images.

Table 4: Results of bipolar detection

Classification through	Features	Model trained through	Parameters (millions)	Testing accuracy (%)	Validation accuracy (%)	Remarks
Frames	Noisy frames of the dataset	Rest-net 18	140	100	100	Over-tuned
		Squeeze-net	129	100	100	Over-tuned
		Alex-net	63	100	100	Over-tuned
		The Proposed CNN-based model	2.7	100	100	Over-tuned
	Frames having aligned faces	Rest-net 18	10	93.0	98.0	Validated
		Squeeze-net	9.2	98.0	97.0	Validated
		Alex-net	11	89.0	96.0	Validated
		The Proposed CNN-based model	2.7	99.4	98.7	Validated
Features	Pose (8 features)	SVM with fine Gaussian	–	97.0	99.0	Validated
	Gaze (300 features)	SVM with fine Gaussian	–	95.6	93.0	Validated
	AUs (29 features)	SVM with cubic kernel	–	92.0	98.0	Validated
	Landmark features (150 features)	SVM with fine Gaussian	–	99.0	96.0	Validated
	Combined (Pose + Gaze + AUs + Landmark)	SVM with cubic kernel and fine Gaussian	–	99.9	99.9	Validated
	Pose (8 features)	DT	–	95.0	94.0	Validated
	Gaze (300 features)		–	96.0	96.0	Validated

(Continued)

Table 4 (continued)

Classification through	Features	Model trained through	Parameters (millions)	Testing accuracy (%)	Validation accuracy (%)	Remarks
	AUs (29 features)		–	94.0	95.0	Validated
	Landmark features (150 features)		–	96.0	92.0	Validated
	Combined (Pose + Gaze + AUs + Landmark)		–	95.0	92.0	Validated
	Pose (8 features)	KNN	–	90.0	95.0	Validated
	Gaze (300 features)		–	98.0	94.0	Validated
	AUs (29 features)		–	95.0	92.0	Validated
	Landmark features (150 features)		–	99.0	98.0	Validated
	Combined (Pose + Gaze + AUs + Landmark)		–	99.0	96.0	Validated

The results from our model are compared with other recent studies on detecting bipolar disorder from videos and images, shown in Table 5.

Table 5: Comparison of the results with the state-of-the-art studies

Reference	Problem addressed	Dataset	Methodology	Evaluation measure
[6]	BD & Depression	BD Corpus and the Well-being	Audio-visual LSTM, audio-visual-textual LSTM & adaptive nonlinear judge classifier	F1 = 0.870, Accuracy = 91.7% & Accuracy = 91.7%

(Continued)

Table 5 (continued)

Reference	Problem addressed	Dataset	Methodology	Evaluation measure
[17]	BD & BPD	82 participants BP, 52 as BPD and 53 as comorbid BP/BPD	ML algorithm	Accuracy (BD/BPD = 79.6%, BPD/BD = 61.7%)
[9]	Bipolar Outpatient	Bipolar Outpatient Clinic in the Medical Faculty at Eskişehir Osmangazi University, Turkey	Polyhedral Conic Functions algorithm	Accuracy = 78.0%
[18]	MDD & BD	81 BD and 127 MDD	Machine learning predictive models	AUC = 0.97 Accuracy (MDD = 92.0% and BD = 86.0%)
[11]	BD	AVEC-2018	CNN, LSTM	UAR = 60.7%
[12]	Hypomania, and Mania	AVEC-2018	Fisher Vector encoder	UAR = 57.4%
[13]	BD	AVEC-2018	IncepLSTM	Accuracy = 65.0%

The proposed model	Locally developed	Bipolar videos	Clinical methodology (self-rating Bipolar scale) + CNN+ SVM+KNN+DT	Accuracy
				SVM = 99.9%
				CNN = 98.9%
				DT = 98.9%
				KNN = 98.7%

4.2 Discussion

In this study [6], an audio-visual LSTM & audio-visual-textual LSTM, both architectures based on recurrent neural network architectures (RNN) used to recognize BD and depression from two datasets, i.e., the BD Corpus and the Well-being dataset. Achieved results Using audio-visual LSTM from BD corpus's as per accuracy = 91.6%, and from Well-being dataset's as per F1 score = 0.870, and feed-forward neural network based adaptive nonlinear judge classifier used, achieved results from this classifier as per accuracy = 91.7%. This study improved by adding different samples (audio, visual and textual) of the same patients.

This study [17] classified BD, BPD and combined BP/BPD patients Using the ML algorithm. The diagnostic accuracy of ML was 79.6% for distinguishing between BD/BPD and 61.7% for BPD/BD. The accuracy of the results is low. This study [9] includes people who met the inclusion criteria at the Bipolar Outpatient Clinic of Eskisehir Osman Gazi University, Turkey. The Polyhedral Conic Functions algorithm was used to classify participants based on six CANTAB neurocognitive tests.

This study achieved 78.0% of bipolar patients distinguished from healthy controls. The accuracy of this study is quite low. In another paper [18], MDD and BD were detected Using a machine learning predictive model. Achieved results as per AUC = 0.97, accuracy (MDD = 92.0%, BD = 86.0%). Patients were recruited from a single center and ethnic group, limiting generalizability.

Although another study [11], the benchmark dataset AVEC-18 is used to classify the BD state. CNN is used for the classification of facial features from video recordings. LSTM is used to classify extracted features from facial images and achieved results from this proposed model as per UAR = 60.7%. Single modalities (Facial images) are used for classification. In another study [12], Fisher Vector encoding features were extracted Using multimodal fusion and OpenSmile. Achieved results Using Fisher Vector encoding as per UAR = 57.4% Achieved UAR are not very high. In another study [13], the IncepLSTM framework was used to categorize BD severity. CNN with different filters were used to classify BD patients, and LSTM was used to classify extracted features. Results achieved Using IncepLSTM as per accuracy = 65.0%. They achieved accuracy Using IncepLSTM id low.

The proposed study refers to implementing its own designed CNN-based model and state-of-the-art CNN-based models that have already been developed. Experiments have been done in several ways. Both pre-trained and reported models are utilized to classify the noisy dataset. Models get overturned on noisy datasets in both ways. OpenFace is a tool for aligning faces and extracting features from noisy datasets. The aligned faces are classified using the proposed model and achieved a validation accuracy of 98.9%. Meanwhile, the SVM, KNN, and DT models have been used to classify extracted features and obtained validation accuracy of 99.9%, 98.7%, and 98.9%, respectively.

5 Conclusion and Future Work

Bipolar disorder is one of the most severe mental health issues people face. Significant indicators of mania or depression can be found in facial AUs, which can aid in diagnosing bipolar disorder. Although several research has attempted to predict the detection of bipolar disorder from these visual cues, their models have not fared well on evaluation measures. Thus, they proposed a CNN and SVM-based multimodal bipolar detection system trained on a locally collected dataset. The experimental results showed a validation accuracy of 98.9% for the proposed CNN model and the extracted features Using SVM, KNN, and DT with an accuracy of 99.9%, 98.7%, and 98.9%, respectively. Also, the outcomes demonstrated the stated method's superiority over the current best practices. Real-time bipolar detection from low-resolution digital camera videos is made more accessible by the proposed lightweight CNN-based model, which has fewer layers and parameters but is perfectly tuned to provide robust performance.

In the future, speech, gait, written samples, and MRI scans will be employed for the classification of mental diseases, and more disorders will be detected using customized CNN, other CNN-based pretrained models, and standard machine learning models, such as SVM, KNN, DT, etc.

Acknowledgement: The researchers would like to thank the BVH Hospital, Bahawalpur, Pakistan staff for their cooperation in providing the dataset.

Funding Statement: Self-funded; no external funding is involved in this study.

Author Contributions: G.G. gave the idea of the research topic, selected the title name, and assisted in the whole research work; S.C. wrote the paper and made a model to perform experiments on the dataset. A.L. helped in the writing of literature review. Similarly, A.S. and M.A. helped in datasets collection from different private and Government hospitals. H.U. and D.O. helped in finalizing & validating the outcomes of the conducted research work.

Availability of Data and Materials: The dataset was obtained from BVH Bahawalpur and other private hospitals. It is not publicly available yet, because of some codal formalities and legal involvements.

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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