

# Anomaly Detection from Medical Signals and Images Using Advanced Convolutional Neural Network

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## Research

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# Abstract

In the field of Artificial Intelligence (AI), deep learning is a method falls in the wider family of machine learning algorithms that works on the principle of learning. Convolutional Neural Networks (CNNs) can be used for pattern recognition from different images based on deep learning. Anomaly detection is a very vital area in medical signal and image processing due to its importance in automatic diagnosis. Anomaly detection from medical EEG signals based on spectrogram and medical corneal images are tested and evaluated in this paper. Technically, deep learning CNN models are used in the train and test processes, each input image will pass through a series of convolution layers with filters (Kernels), pooling, and fully connected layers (FC) for the classification purposes. The presented simulation results reveal the success of the proposed techniques towards automated medical diagnosis.

## Introduction

In the field of medical signal and image processing, automatic diagnosis is the main and most important task. Automatic diagnosis depends on the detection of anomalous behavior in signals or images. For example, EEG signals can reflect the status of epilepsy patients. At certain times, it is possible to detect or predict seizure periods based on anomaly detection techniques. In another example of medical image processing, anomaly detection techniques can be used to locate exudates and micro-aneurysms in optical fundus images. The common thread between these trends is how to develop efficient tools for automated diagnosis of abnormal activities in medical signals or images.

Convolutional neural network (CNN) is one of the most effective deep learning methods to solve image classification problems and it is one of the most widespread deep neural networks models that owns the capability of learning features automatically from input data. At this paper, we will discuss how CNN can detect the anomalies from the images and the signals. CNN consists of convolutional layers followed by activation function, pooling layers, dropout layers, and fully connected layers. The convolutional layer is contained filters that are used to perform a two-dimensional (2D) convolution with the input image. Feature maps are generated from the convolution layer. The pooling layer decreases the size of the image. The used value is the maximum or mean value of the pixels. The max-pooling layer is used in this technique. The inclusion of a dropout layer is used a regularization technique for reducing over fitting.

Epileptic seizures are the results of the transient and unexpected electrical disturbance of the brain. Approximately, one in each 100 persons can experience a seizure at least once. Unfortunately, the occurrence of an epileptic seizure is unpredictable, and its process is not totally understood. EEG is a representative signal containing information of the electrical activities of the brain. EEG is the most commonly used signal to clinically assess brain activities. The detection of epileptic form discharges within the EEG is a vital task within the diagnosis of epilepsy. The detection of epilepsy with visual scanning of EEG recordings for the spikes and seizures is extremely time consuming, particularly in the cases of long recordings. Therefore, the extraction of EEG signal parameters using computers is extremely helpful in automatic diagnosis.

In the proposed work, the original EEG signals are converted to images using spectrogram and then the resulted spectrogram images are directly input into the CNN instead of extracting all feature types. We tested this method on three patients in the scalp CHB-MIT database. We are not only detecting binary epilepsy scenarios, e.g., Normal vs. Seizure and Normal vs. Pre-ictal, but also verified the ability to classify a triple case, e.g., Normal vs. Seizure vs. Pre-ictal.

The rest of this paper is organized as follows. Section 2 presents the proposed approaches for corneal image detection of anomalies with CNN and EEG signal detection and predication with CNN. Section 3 presents the specifications of the employed datasets. Section 4 presents the simulation results. Finally, the concluding remarks are given in Sect. 5.

## Methods

This section will show two successfully models for the convolutional neural networks which are exploited for anomaly detection from medical EEG signals based on spectrogram and from medical corneal images.

### Corneal Image Detection of Anomalies with CNNs

Cornea is the transparent portion through which the light enters the eye. Cornea and Sclera form the outer tunic of the eye and are mechanically strong. They act a protective shield and prevent the foreign objects from entering the eye. Cornea has five main layers, namely: (1) Epithelium, (2) Bowman's layer, (3) Stroma, (4) Descemet's membrane, and (5) Endothelium. The main function of the endothelium is to pump the excess water out of the stroma to preserve its mechanical structure and optical clarity. The corneal endothelium is the inner layer of the cornea and it is of great interest for ophthalmologists. This layer is formed by closely packed, predominantly hexagonal cells whose shape and structure can provide important diagnostic information about the cornea health status or indicate some corneal diseases. The corneal endothelium is a monolayer of cells which has a big impact on the human vision. It is responsible to assure proper hydration of the eyeball and in consequence by providing sufficient amount of water [1-3].

Eye disorders among the elderly are a major health problem. With advancing age, the normal function of eye tissues decreases and there is an increased incidence of ocular pathology. Corneal is a complication of refractive surgery characterized by the cloudiness of the normally clear cornea. Computer based intelligent system for classification of these eye diseases is very useful in diagnostics and disease management. Corneal disease is a serious condition that can cause clouding, distortion and eventually blindness. There are many types of corneal disease. The three major types are keratoconus, Fuchs' endothelial dystrophy, and bullous keratopathy. (1) Keratoconus is weakening and thinning of the central cornea. The cornea develops a cone-shaped deformity. Progression can be rapid, gradual or intermittent. Keratoconus usually occurs in both eyes, but occur in only one eye. (2) Corneal endothelial cells (CECs) are terminally differentiated cells, specialized in regulating corneal hydration and transparency. They are highly polarized flat cells that separate the cornea from the aqueous humor. (3) Fuchs' endothelial

dystrophy is hereditary abnormality of the inner cell layer of the cornea called the endothelium. (4) Bullous keratopathy is a condition in which the cornea becomes permanently swollen. This occurs because the inner layer of the cornea, the endothelium, has been damaged and is no longer pumping fluids out of the tissue.

M. Tang 2005, V. Girisha 2016, and I. Mohammed 2006 display the corneal disease that can cause some disaster cases such as clouding, distortion or blindness. The major types of the endothelium diseases are the following: (1) Keratoconus is weakening and thinning of the central cornea. (2) Corneal endothelial cells (CECs) are terminally differentiated cells and transparency. (3) Fuchs' endothelial dystrophy is effect at the inner layer for the cornea which called the endothelium. (4) Bullous keratopathy is a condition in which the cornea becomes permanently swollen. This occurs because the inner layer of the cornea, the endothelium, has been damaged and can't pumping fluids out of the tissue, various techniques used at this article such as histogram, enhancement, and segmentation for the images for enhancing the quality of the images. The results from this classification with accuracy 83% for Fuchs 'dystrophy, 77% for Guttation, 82% for Iridocorneal, 82% for Posterior dystrophy [4-6].

In G. Ayala 2001, R. Nadachi 1992, and F. Sanchez 1999, the image preprocessing techniques are presented to improve the image quality. Several previous solutions for segmentation of endothelial image have already been introduced. Their aim is to delineate cell borders using such techniques as: Numerical measures for corneal cells using Wavelet transform, Local greyscale thresholding followed by scissoring and morphological thinning [7-9].

1. Mahzoun 1996, K. Habrat 2016, and A. piokowski 2017 used some techniques such as active contours, or analysis local pixel levels aimed at finding intensity borders between cells, calculating the corneal cells and their inter relationship, cell density, coefficient of variation, hexagonally, exploits the features that endothelium cells are approximately laid out as a regular tessellation of hexagonal shapes. These techniques estimate the inverse transpose of a matrix generating the cellular lattice [10-12].
2. kannathal *et al.* 2006 presented a comparison between three classifiers for corneal images, artificial neural network ANN with accuracy 89% and fuzzy classifier 92.94% and adaptive neuro fuzzy classifier 92.94% and they trained 30 normal images and 50 abnormal images. A. Piorkowski *et al.* 2016 presented a method for corneal endothelial images segmentation based on automated analysis of cornea endothelial cell images. A preprocessing step was done for edge regularization by using filtering technique. The cell's borders are then determined using the directional filter [13-14].

Alferdo Ruggeri, Enrico Grisan, 2005, and Marco 2002 presented a solution to the problem of automatic estimation of endothelial sell density from corneal images. They proposed methods that the spatial frequency existed in digital endothelium images is extracted with a 2-D Discrete Fourier transform (DFT) technique. The cell density is related to a circular band in the DFT of the images which contain the frequency information and the goal of Gavet article, 2008 to compute the borders of the cornea cells based on NN technique. Greyscale specular microscopic images of corneal endothelial cells are used for

evaluating this algorithm. The disadvantage of the neural network technique is the use of fixed-size mask which needs to expert to perform the necessary corrections while Gavet article compute the borders of the cornea cells automatically [15-17].

Enrico Grisan and Anna Paviotti 2005 proposed a new method to calculate endothelium cell density which is one of the main indicators of cornea health state and quality. This article exploits the property that endothelium cells have approximately a regular tessellation of hexagonal shapes. This approach evaluates the inverse transpose of a matrix creating this cellular lattice and then from this cellular lattice the cell density can be easily obtained. This information could be easily extracted if the cell contours are well defined in the image. There are other methods to classify the corneal images based on the corneal curvature [18-20].

Fabijańska 2019 introduced an approach to study the corneal health status based efficient automatic segmentation of corneal endothelial images. They used a combination of neural network to determine the pixel location at the cell boundaries with post processing stage to obtain the edginess map. They exploited morphological operations with local thresholding for images segmentation. They achieved acceptable results compared with ground truths [21-24]. Table 1 shows a comparison between different classification techniques according the accuracy.

**Table 1** Comparison between different classification techniques.

Our proposed approach is based on building an efficient deep learning model that can distinguish between both normal and abnormal states of person's retina. The proposed model consists of 5 CNV layers followed by 5 max pooling layers. Finally, a global average pooling is used. Table 1 shows the model summary for each layer and its output shape. Images are input in 224×224. Layers have number filters of 16, 32, 64, 128, and 256 for layers 1, 2, 3, 4, and 5, respectively. Finally, a dense layer with size of 2 is used for classification decision as shown in Fig.1.

Fig. 1 Layers of the proposed deep learning model.

This model is implemented for small retinal dataset. The dataset is divided into 80% training and 20% for testing. The proposed CNN is summarized in Table 2. This table shows the output of each layer of the proposed deep learning CNN model.

**Table 2** Summery of proposed deep learning model.

## Eeg Signal Detection And Predication With Cnns

Epilepsy is a neurological disease that is not contagious, it is not a mental illness, and it is not a developmental disability. A seizure is a brief disruption of electrical activity in the human brain. Epileptic seizures can also be defined as a deformity in the human brain that makes the patient prone to seizures, which usually are frequent and recurrent [25, 27].

Research studies provided by World Health Organization (WHO) shows that approximately 50 million people suffers from epilepsy worldwide. The estimated proportion of the general population with active epilepsy (i.e. continuing seizures or with the need for treatment) at a given time is between 4 and 10 per 1000 people. However, some studies in low and middle-income countries suggest that the proportion is much higher, between 7 and 14 per 1000 people [28].

Electroencephalography (EEG) is the recording of electrical activity along the scalp produced by the discharging of neurons within the brain. EEG refers to the recording of the brain's spontaneous electrical activity over a period. When brain cells (neurons) are activated, local current flows are produced. EEG detects the electrical activity using small, and flat metal discs (electrodes) attached to the brain scalp. The brain cells send electrical impulses and are active all the time, even when human sleeping [29, 31].

Automatic seizure detection and prediction from EEG have received considerable research focus because of their importance for better understanding of epilepsy and more efficient management of the disease. Feature extraction is a key step in determining EEG classification for detection or prediction. We imagine courageously a method in which classification is carried out without complex feature extraction, and the recent development of CNN has provided a new way for addressing this issue.

Dalton *et al.* (2012) presented a Body Sensor Network (BSN) that can detect seizure signal from statistics obtained from signal in the time domain, with sensitivity of 90% and specificity of 84% [8]. There are several seizure detection methods based on frequency domain. Khamis *et al.* (2013) presented a technique using frequency-moment signatures to detect patient-specific seizures with sensitivity of 91% [31-32].

Wavelet transform is applied in several techniques. Shoeb *et al.* (2004) used a wavelet decomposition to obtain a feature vector of EEG signal. Meier *et al.* (2008) used a Support Vector Machine (SVM) combining a wavelet and time features. Abibullaev *et al.* (2010), Zandi *et al.* (2010) Gue *et al.* (2010), Orhan *et al.* (2011) and many others applied wavelet transform with different classifiers like Artificial Neural Network (ANN) and cumulative thresholds. Zhou *et al.* (2013) proposed another technique using lacunarity and Bayesian linear discriminant analysis for seizure detection with sensitivity of 96.25% [32-34].

Vidyaratne *et al.* (2016) proposed Cellular Neural Networks and Bidirectional Recurrent Neural Networks to extract temporal features for seizure analysis [26]. Shoeb and Guttag (2010) presented a patient-specific machine learning technique based on the CHB-MIT database. They extracted spectral and spatial features and then combined non-EEG features to form a feature vector; an SVM was then used for classification. Their approach detected 96% of 173 test seizures in an event-based assessment [27]. Pramod *et al.* (2014) and Turner *et al.* (2014) used deep belief networks applied on multi-channel EEG data for seizure detection [34-36].

We present an efficient approach for simultaneous channel selection and activity detection from EEG signals adopting CNN. The proposed approach depends on generating spectrograms of EEG signal

segments. Different channels are considered in three scenarios; three-state classification, seizure detection and seizure prediction. A CNN model is developed for classification of spectrograms. The highest recorded classification accuracy is adopted as the channel selection criterion.

A spectrogram is a visual representation of the spectrum of frequencies as they vary with time or other variables; it shows how the frequency content of a signal changes with time. The spectrogram graph shows the energy content of a signal expressed as function of time and frequency. The produced graph shows an amplitude-dependent colors in which the horizontal and vertical axis is time and frequency. Spectrogram of an EEG signal is an estimation of the time evolution of the EEG frequency content

The first step to calculate the spectrogram is to segment the EEG signal to equal length windows, which may not overlap but usually overlapped in various ways, the window size should consider the nonstationary nature of the EEG signal. The idea here is that the spectral properties of an EEG non-stationary signal can be displayed through a series of spectral snapshots. As a nonstationary signal, EEG frequency change with time, the segment length (time resolution) must be short enough in which the frequency change is not remarkable.

Next step in signal analyzer is to compute the spectrum to get the short-time Fourier transform. Finally, the power of each spectrum is displayed segment by segment; these spectrums laid side by side to form the image a magnitude-dependent color map is produced as an image. This image depicts the spectrogram of each signal.

The proposed approach is based on building an efficient model that can distinguish between three-states classification, detection process, and prediction process. The proposed model consists of Convolutional layer followed by max pooling layers. Finally, a global average pooling is used. Images are input in  $224 \times 224$ . One convolutional layer has no. of filters 32 and max. pooling with size 2. Finally, a dense layer with size of 3 is used for classification decision for three-states classification and with size 2 for classification decision for detection and prediction process as shown in Table 3.

**Table 3** Specifications of layers.

In the proposed model, we design a CNN with no more than three layers due to that a simple training structure is more conducive to the online clinical diagnosis of epileptic signals. The proposed approach is tested on three patients. During each run, 70% is used for training and 30% for testing. In three-states classification, there are three total categories with 90 total images. There are 63 training images and 27 test images. And in two-states classification, there are two total categories. There are 60 total images. There are 42 training images and 18 test images.

## The Utilized And Tested Datasets

The utilized EEG database is from CHB-MIT [CHB-MIT Scalp EEG Database, [Online]. Available: <http://physionet.org/physiobank/database/chbmit/>], the recordings were collected from 23 children with

epilepsy using scalp electrodes, and EEG data were provided by the Massachusetts Institute of Technology (MIT, USA). The sampling frequency for all patients was 256 Hz.

The period in which patients experience the onset of seizure is called the ictal state. The inter-ictal period is the normal state of two seizures. The pre-ictal period is the transition from the inter-ictal to the ictal period. The detailed information of the used three patients (chb01, 08 and 20) are as shown in Table 4. These cases have different number of seizures. Corneal data set based on Endothelial Cell Alizarine online images Available: <http://bioimlab.dei.unipd.it/Endo%20Aliza%20Data%20Set.html>.

Figure 2 shows samples of normal and abnormal corneal images.

**Table 4** The used data set description.

**Fig. 2** Sample frames of retinal images. (a), (b) are normal images, (c), (d) are abnormal images.

## Results And Discussion

In the proposed approaches, accuracy is used to estimate the strength of the CNN model. Accuracy is calculated as follow:

$$Accuracy = \frac{\text{No. of images that were accurately classified}}{\text{Total No. of images}} \times 100 \quad (4)$$

### Corneal Image Classification Results:

The proposed approach consists of 5 convolution layers followed by five max pooling layers and a global average pooling layer is used before the dense layer at the last decision soft max layer. Figures 3 and 4 show the accuracy and loss during the training phase. It can be observed that the accuracy reached 100% and the loss decreased near to be zero. Our proposed system illustrates comparable results with other techniques in the literature.

**Fig. 3** Resulting accuracy of the proposed deep learning model.

**Fig. 4** Resulting loss of the proposed deep learning model.

### EEG Signals Classification Results:

The proposed approach consists of a convolutional layer followed by max pooling layer are used before the dense layer at the last decision soft max layer. Simulation results are performed using python, Keras, Pillow, and Tensorflow.

The methodology described is evaluated using the CHB-MIT databases based on time domain signal. This system is tested on three cases: two types of experiments involving two-states classification

problems ((i) Normal vs. Pre-ictal and (ii) Normal vs. Seizure) and one three-state classification problem (Normal vs. Seizure vs. Pre- ictal). We trained and tested our method for each 23 channels for three patients individually, after applying the spectrogram for them and the accuracy of classification results for all channels for the three patients analyzed are presented in Tables 3 through 5 and Figures from 3 through 5.

Table 3 reports the accuracy classification results for 23 channels of Patient number 1 who has 7 epileptic seizures. For three-states and detection process, the best classification result was observed for channel 11, while the other channels had poor results. And the accuracy of results obtained were 74.07% and 94.44%, respectively. For prediction process, the best classification result was observed for channel 06 with the accuracy of result obtained was 94.44%, while the other channels had poor results.

Table 4 reports the accuracy classification results for 23 channels of Patient number 8 who has 5 epileptic seizures. For three-states classification, the best classification result was observed for channel 23 with the accuracy of result obtained was 70.37%, while the other channels had poor results. For detection classification, the best classification result was observed for channel 15 with the accuracy of result obtained was 72.22%, while the other channels had poor results. While for prediction process, the best classification result was observed for channel 03 with the accuracy of result obtained was 88.89%, while the other channels had poor results.

Table 5 reports the accuracy classification results for 23 channels of Patient number 20 who has 8 epileptic seizures. For three-states classification, the best classification result was observed for channel 09 with the accuracy of result obtained was 70.37%, while the other channels had poor results. For detection classification, the best classification result was observed for channel 03 with the accuracy of result obtained was 77.68%, while the other channels had poor results. While for prediction process, an accuracy of 94.44% was achieved for seven channels, such as channels 01, 04, 15, and 20. Ideal results with 100% were obtained for six channels, such as channels 03, 17, 21, and 23.

**Table 5** The accuracy results for patient 1.

**Fig. 5** The accuracy results for patient 1.

**Table 6** The accuracy results for patient 8

**Fig. 6** The accuracy results for patient 8.

**Table 7** The accuracy results for Patient 20.

**Fig. 7** The accuracy results for patient 2.

## Conclusions

This paper has dealt with a very vital track in medical signal processing, which is the automated diagnosis from signals and images. We have introduced efficient anomaly detection techniques based in CNN for both EEG and corneal images. The proposed approaches for seizure detection and prediction have been evaluated on CHB-MIT database and achieved success rates up to 100% in seizure detection and prediction. Moreover, the corneal images detection approaches managed to achieve efficient detection of anomalous behavior in the corneal images. The track presented in the paper is a good step towards automated diagnosis systems.

## Abbreviations

CNNs:Convolutional Neural Networks; FC:fully connected layers; CECs:Corneal endothelial cells; DFT:Discrete Fourier transform; WHO:World Health Organization; BSN:Body Sensor Network; ANN:Artificial Neural Network

## Declarations

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### Authors' contributions

All authors took part in the discussion of the work described in this paper. All authors read and approved the final manuscript.

### Availability of data and materials

Not applicable.

### Competing interests

The authors declare that they have no competing interests.

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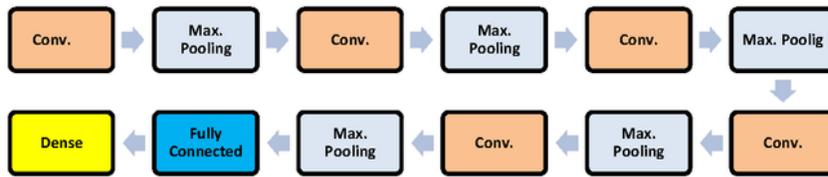
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## Tables

Due to technical limitations, all tables are only available for download from the Supplementary Files section.

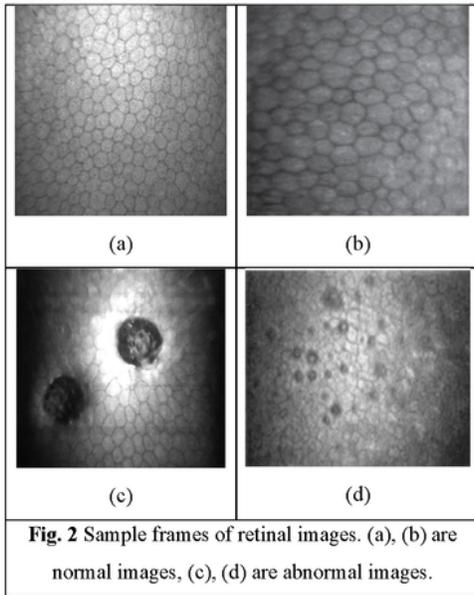
## Figures



**Fig. 1** Layers of the proposed deep learning model.

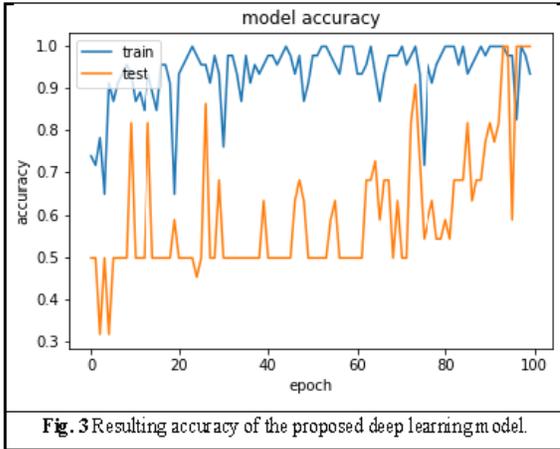
## Figure 1

Layers of the proposed deep learning model.



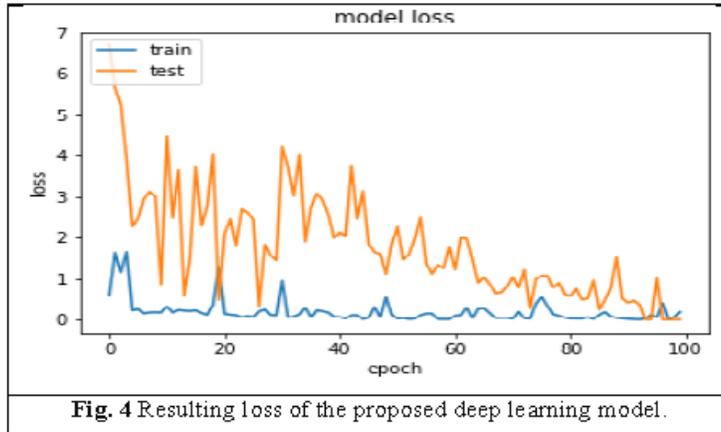
**Figure 2**

Sample frames of retinal images. (a), (b) are normal images, (c), (d) are abnormal images.



**Figure 3**

Resulting accuracy of the proposed deep learning model.



**Figure 4**

Resulting loss of the proposed deep learning model.

Fig. 5 The accuracy results for patient 1.

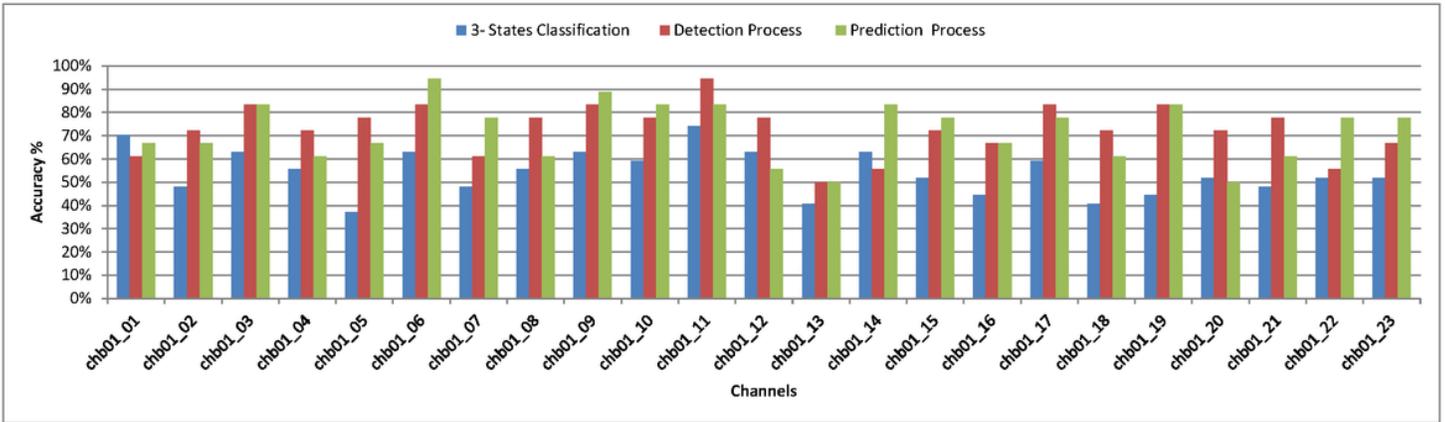


Figure 5

The accuracy results for patient 1.

Fig. 6 The accuracy results for patient 8.

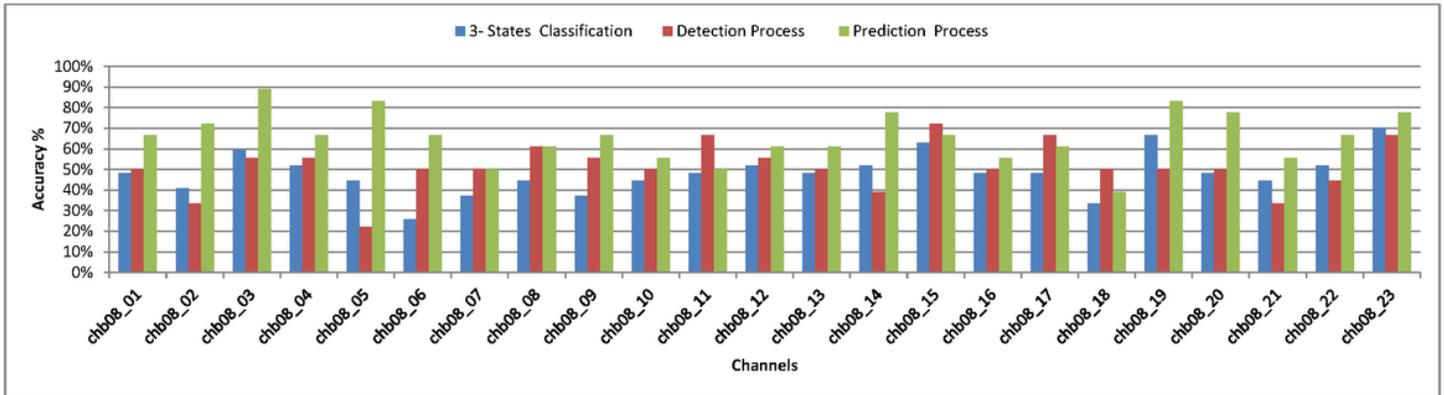


Figure 6

The accuracy results for patient 8.

Fig. 7 The accuracy results for patient 2.

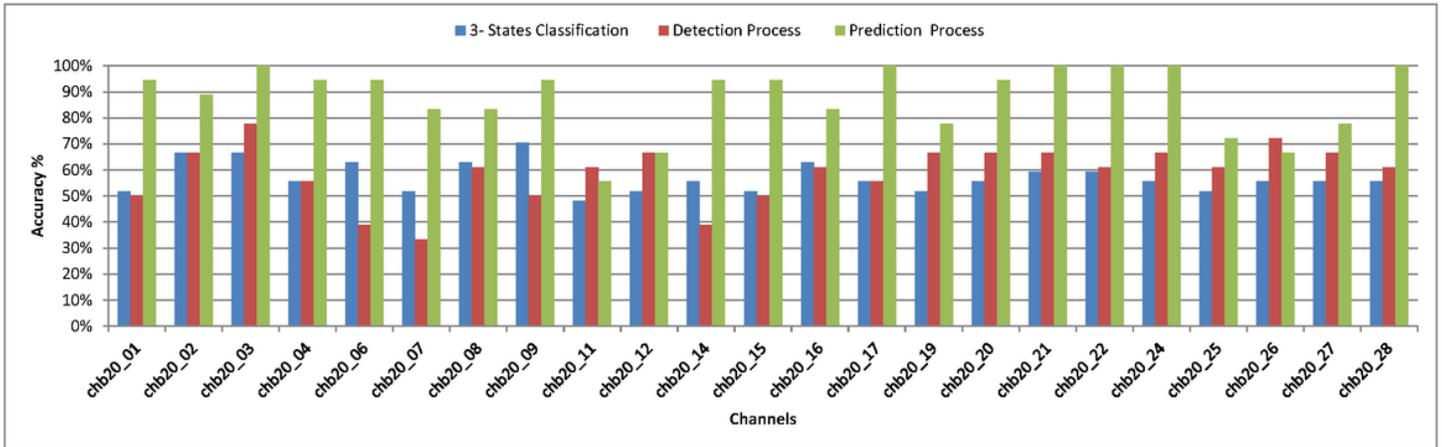


Figure 7

The accuracy results for patient 2

## Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [Table1.docx](#)
- [Table3.docx](#)
- [Table5.docx](#)
- [Table6.docx](#)
- [Table7.docx](#)
- [Table4.docx](#)
- [Table2.docx](#)