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Detection and Classification of the Schizophrenia with Ocular Artifacts Removal in EEG Signal with Darknet YOLO architecture

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Abstract: Schizophrenia is a devastating mental illness that affects millions of people throughout the world and profoundly alters the way they think, feel, and act. The illness may be accurately diagnosed thanks to the EEG signal. Researchers can capture brain activity non-invasively using an electroencephalogram (EEG). It's a useful technique for diagnosing a wide range of neurological illnesses and diseases of the brain. An electrooculogram, a large electrical potential around the eyes produced by blinking or eye movement, is recorded. When extracortical activity spreads to the scalp, it contaminates EEG data. Ocular artifacts are a term used to describe these Ocular artifacts (OAs). When it comes to EEG analysis, one of the most significant types of interference is the ocular artifact. An important part of the analysis before processing EEG data is OAs removal/reduction. To eliminate the common classical OAs, a multi-channel EEG or a second electrooculogram recording is required. This paper developed a Fejer-Korovkin pre-processing model for OA elimination in the EEG signal. The developed model has termed the FK_DARKNET model with DARKET integrated with the RCNN (Recurrent Convolutional Neural Network) applied over the YOLO architecture. The proposed FK_DARKNET comprises the YOLO model for the classification of Schizophrenia and normal EEG signals in the images. The proposed FK_DARKNET model's efficacy is evaluated in light of the state-of-the-art method. The results of the comparison show that the suggested FK_DARKNET performs better than its competitors in terms of accuracy, TPR, and TNR.

Keywords: *EEG, RCNN, YOLO, DARKNET, Classification*

I. Introduction

In all, more than 21 million individuals across the world are affected by schizophrenia, making it a common chronic mental illness [1-2]. Distractions in thought, perception, and behaviour are hallmarks of this condition. Schizophrenia patients often have psychotic symptoms like hearing voices or having odd beliefs, and they may seem to be disconnected from reality. A person suffering from this mental illness may be unable to make a living or have their education disrupted due to its incapacitating symptoms. You're more likely to have symptoms in your late teens or early twenties, when you're about 16 or 17. Schizophrenic patients have a 2–3-fold increased risk of death compared to the general population, and 69% of them get no treatment at all. The majority of them reside in nations with poor or medium incomes, making it difficult for them to obtain mental health services. Using electrodes on the scalp, electroencephalography (EEG) [3-4] records electrical activity in the brain non-invasively throughout time. Eye movements captured by electro oculograms obscure EEG signals more than other artifacts in EEG recordings, which are polluted by biological artifacts. Ocular artefacts have a far larger amplitude than EEG signals. To properly interpret EEGs, it is critical to separate the EEG signals from the EOG signals.Ocular artifacts are EEG artifacts caused by ocular activity and are among the most troublesome of the artifact signals (OAs)[5-6]. To make data collection and analysis more difficult, OAs may obstruct the EEG signal visually or repeatedly. Furthermore, OAs have been shown to reduce the accuracy of BCI classifications. Many OAs may be seen in EEG data. While collecting EEG data, blinking/movements of the eyes are unavoidable. Eye and brain cortical surface electric fields are altered as a result of these motions. The OAs are generated, and EEG signals overlapped when these movements are captured by the scalp EEG electrode. Many characteristics of EOG signals are similar to those of OAs, such as the spike-like form in the low-frequency regions and the brief duration. Cleaning up EEG signals from contamination is a difficult task because of the non-measurable interference caused by organic compounds (OAs). In contrast to EEG, which has a much smaller amplitude than OAs, which may be a breakthrough in the elimination of OAs. To conduct neurophysiological monitoring or EEG data processing, OAs elimination is required. In reality, several methods for recovering an artifact-free signal have been thoroughly studied in

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recent years. It was standard practice early on to manually trim the whole data segment impacted by OAs, which resulted in significant information loss [7].

This paper proposed an FK_DARKNET architecture elimination of the OA in the EEG signal and classification of the EEG signal waveform as Schizophrenia or normal. The proposed model comprises the RCNN model for segmentation of the waveform in the EEG signals. Additionally, to improve feature extraction and classification YOLO architecture based DARKNET model is implemented for the classification and processing of Schizophrenia in the EEG images. The proposed FK_DARKNET architecture process the input EEG signal and perform classification with the YOLO model. This paper is organized as follows: In section II presented the overall literature review of the paper related to feature extraction and classification. In section III research methodology adopted for the developed FK_DARKNET is presented. The performance matrices and comparative analysis for the proposed FK_DARKNET are presented in section IV along with simulation results. The overall conclusion is given in section V.

II. Related Works

Diverse techniques exist to get rid of polluted EEG signals' Ocular artifacts. Researchers in [8] examined the EEG data collected at construction sites may include artifacts that can be detected and removed using a DCA framework. For detecting and reducing EEG artifacts linked to the eyes, the proposed DCA-based approach includes ICA and PCA. The findings showed that the DCA technique was superior to the ICA when it came to obtaining high-quality EEG data on construction sites. The results showed that when compared to the ICA- and PCA-filtered signals, the DCA-filtered EEG signal was the closest to the reference EEG signal. The DCA method has been widely adopted on construction sites as a means of eliminating ocular artifacts and collecting higher-quality EEG data. It's only that the approach requires a more accurate evaluation of employees' psychological conditions including high levels of stress and mental exhaustion. A study conducted in [9], describes a new technique for identifying and avoiding EEG signal ocular artifacts (such as eye movements). The model consists of two parts: (a) detecting ocular artifacts and (b) eliminating them. After the EEG has been decomposed using a 5-level Discrete Wavelet Transform (DWT), ocular artifacts can be located using Empirical Mean Curve Decomposition (EMCD). After the decomposition is completed, further first-order statistical features can be extracted, such as kurtosis, variance, Shannon's entropy, and a few more. In the categorization phase, these characteristics will assist in detection. A machine learning technique known as Neural Network is used to identify ocular artifacts from the deconstructed data (NN). The standard NN ANN training algorithm has been swapped out with a Dual Positioned Elitism-based Earth Worm optimization Algorithm (DPE-EWA) to boost performance. It is recommended to use DPE-EWA and the Lifting Wavelet Transform (LWT) to enhance the filter coefficients during the optimization phase. Therefore, the use of an optimized NN in conjunction with an optimized LWT suggests the potential for identifying and correcting ocular aberrations in an EEG signal.

EEG data for seizure categorization may be extracted using CNN and ocular artifacts, as studied in [10]. We test the method's ability to correctly identify traits using EEG signals from the Bonn dataset, accounting for varying degrees and types of ocular aberrations. According to the findings of the performance assessment, the method's classification accuracy suffers substantially when ocular artifacts are present. Further, observation shows how much more accurate the suggested CNN architecture is than raw temporal EEG data at extracting the discriminating characteristics from spectral EEG signals. For the classification of left/right-hand motions, in [11] used a Multi-layer Perception Neural Network. Extraction of statistical time domain and power spectral density frequency domain characteristics produced an accuracy of 96.02 percent by hand. The results were compared to those of a deep learning framework experiment to see which was the most effective. Precision, F1-Score, and recall were also taken into account as performance measures in addition to accuracy. Unwanted signals pollute the EEG signals, affecting the algorithm's effectiveness. As a result, Independent Components Analysis was used to eliminate the artifacts and improve the performance. Feature vectors that gave satisfactory accuracy were selected. All nine individuals were treated using the same technique. As a consequence, 9 individuals had intra-subject accuracy of 94,72 percent. The findings indicate that the proposed method is effective at correctly classifying motions of the upper limbs.

One novel supervised method for cleaning up EEG data is the evaluation of independent component analysis and discrete wavelet transform for ocular artifacts [12]. The EEG data were collected from 29 people in an open setting as they walked about and made gestures and facial expressions while watching movies. To identify chunks including eye movements, thirteen morphological characteristics were derived from the collected EEG data. Further processing of the EEG chunks including eye movements is done to eliminate noise without altering the signal's shape. Using eye movements as a test case, the suggested technique outperforms other methods based on wavelet augmented independent component analysis in terms of correlation, mutual information, phase difference, and computing time. Statistical characteristics such as sensitivity and specificity were also calculated, and their results indicate how reliable the suggested strategy is as a whole.

In [13], it was proposed that the JADE method's independent components may be isolated using a hybrid ICA and Kalman Predictor algorithm to eradicate OA. A mat lab implementation of the suggested design was used, and the MSE of the proposed Kalman technique was found to be much lower than that of ICA and ANC. In [14] presented a novel technique for rapidly removing OAs from multichannel EEG to improve the signal-to-noise ratio (SNR). OAs may be extracted from EEG using the moment matching technique, which is often used to remove stripe noise from hyper-spectral pictures. In this novel technique, the locations at which multiple EEG channels are sampled are analogized to pixels in an image. EEG propagation features are used to rectify OA-induced changes in EEG propagation. Improved moment matching (IMM) outperforms independent component analysis (ICA) and second-order blind identification at minimizing OAs and conserving information present in the EEG waveform, as shown by mathematical derivation and empirical confirmation of the results. In the frontal area most negatively influenced by OAs, the SNR increased by 138.1 percent compared to ICA, and the average SNR increased by 58.7 percent. Furthermore, real-time and offline processing benefit from the system's low latency. An advantage of IMM is that it helps remove OAs while also enhancing the SNR of multichannel EEGs. IMM provides a new alternative for improving multichannel EEG's signal-to-noise ratio (SNR).

In [15], the semantic segmentation method was suggested to detect and label eye-blink artifacts in EEG recordings. Blink artifact detection in EEG recordings was the first application of the described approach. In this study, public test signal photographs were successful 94.4 percent of the time. Automatic artifact removal and identification in EEGs using deep learning algorithms could significantly reduce the need for human experts. Raw EEG data may contain artifacts that can be exploited by deep learning algorithms. This technology has the potential to replace both visual inspection and traditional machine learning approaches to EEG analysis. To help doctors quickly resolve artifact concerns during signal collection, [16] provides a deep learning model to detect their presence and classify the type of artifact. In order to identify four types of artifacts and the actual signal, the model is tuned to map 1-second segments of raw EEG data. Classification accuracy for binary artifacts using time-lapse is 67.59 percent, with a true positive rate of 80 percent and a false alarm rate of 25.82 percent. The model is small and light, making it a good candidate for use in mobile equipment.

One-dimensional (1D) residual Convolutional Neural Networks (ResCNN) were proposed for raw waveform-based EEG denoising in [17]. For a comprehensive solution, we employ the waveform in and waveform out technique to map a noisy EEG to a clean EEG signal. Standard practice calls for using an objective function to optimize model parameters during training, and then employing the trained 1D-ResCNN model as a noise filter to clean up the contaminated EEG signal during testing. On the basis of EEG signals from the CHB-MIT Scalp EEG Database, the proposed model is assessed together with additional noise signals acquired from the database. The model was compared to others, such as those based on recursive least squares (RLS) filters, Wavelet transforms (WTs), deep neural networks (DNNs), and independent composite analyses (ICAs). The suggested model produces cleaner waveforms and improves SNR and RMSE significantly, according to the results of experiments. The suggested model, on the other hand, can keep EEG signals' nonlinear properties.

In [18] developed a classification model in the brain region with the classification of Schizophrenia and dysfunction. The data were collected from 26 Schizophrenia patients from the Chegdu fourth hospital. The classification of the EEG signal is based on the consideration of the phase-locking value (PLV) along with a bandpass filter for a frequency range of 30 – 40Hz with the reference value of zero. The feature selection is performed with the Random Forest (RF) classifier with an estimation of the F-Score. The performance is comparatively examined with conventional classifiers such as Linear Discriminant Analysis (LDA) and Support Vector Machine (SVM). Based on this in [19] reviewed the machine learning model for EEG Schizophrenia classification model with machine learning model. The analysis of the review expressed that the EEG-based models are effective for the prediction of Schizophrenia. The disorders associated with Schizophrenia are processed effectively through early interventions. To perform classification of the Schizophrenia [20] proposed a RLNDiP model based on the classification with seize. The developed RLNDiP model is based on ethe stimation of the signal in both time and frequency domains. The developed model performs computation with decomposition of the brain signals with the extraction of the features integrated with different fusion and discrimination analysis. The developed model uses the prominent features with

Kruskal-Wallis test ($p < 0.05$). The developed ANN mode evaluated for the classification performance of the Schizophrenia with the improved performance of the classification.

In [21], a unique automated Schizophrenia model was built on the basis of the Collatz Conjecture in order to detect EEG signals. The developed model perform in three aspects such as generation of multilevel features. In second stage adopted iterative neighborhood component analysis (INCA) for estimation of the features. Finally, the selected features are integrated with k nearest

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neighbor classifier (KNN). Similarly, in [22] constructed a generalized regression neural network (GRNN) model for Schizophrenia classification. The estimation is calculated using a 10-fold cross validation approach that takes into account the distance between individual city blocks. Schizophrenia is classified in relation to a "healthy" individual. For the purpose of Schizophrenia categorization, [23] created an Optimized extreme learning machine (OELM) and a resilient variational mode decomposition (RVMD). Table 1 provided a synopsis of the relevant literature

Table 1: Summary of Literature

Reference	Method	Outcome	Limitations
OA DETECTION TECHNIQUE			
[8]	DCA framework for OA estimation	Removes the OA	Accuracy is not adequate
[9]	Using the EEG to diagnose OA	OA and LWT in the EEG signal are optimized.	Complexity is high
[10]	CNN-based OA extraction	Powerful for isolating and labeling EEG OA signals.	Accuracy alone is not sufficient.
[11]	Multi-layer perceptual construction Neuronal System	Accuracy is adequate	Suitable for minimal dataset
[12]	Uses independent component analysis for EEG	Estimation is based on gestures	Accuracy is not adequate
[13]	ICA-Kalman Predictor hybrid	Uses OA classification	Performance is not adequate
[14]	Developed a SNR elimination	SNR is reduced significantly	Latency is increased
[15]	Constructed a semantic segmentation	OA is classified with deep learning model	Accuracy is less
CLASSIFICATION OF SCHIZOPHERENIA			
[18]	Developed a Random Forest based classification model	Classifies Schizophrenia and dysfunction	Accuracy is not adequate
[20]	Proposed RLNDiP model	Classification performs provides 100%	Complexity is high
[21]	KNN based classifier for Schizophrenia	Schizophrenia model classification is performed	Performance is not adequate
[22]	Constructed Generalized Regression Neural Network (GRNN)	Achieves accuracy of 94.80%	Mathematical derivatives are complex
[23]	Proposed a RVMD and OELM classification model	Provides accuracy, precision, specificity, F-1 measure and sensitivity,	Performance is not explained clearly.

Iii. Proposed Darknet Yolo Architecture For Oa Detection And Classification

Fejer-Korovkin filtering is used as preliminary processing in the proposed model to de-noise the IMF components that cause the ocular abnormalities. This model uses real-time spectral analysis of multichannel EEG data to accurately diagnose schizophrenia in patients. Repeatedly filtering out OAs from noisy EEG data allows a trained RNN to pick up on the high-order statistical moments information of the EEG. To remove OA in the EEG signal classification is performed for identification of Schizophrenia. The proposed model incorporates the RCNN_DARKNET architecture for training the computer vision dataset and YOLO for testing. The constructed model comprises correlation-based norm optimization for Schizophrenia detection and classification in the EEG signal. The developed model incorporates the training and testing phases. Figure 1 illustrated the overall flow of the proposed FK_DARKNET for processing is presented.

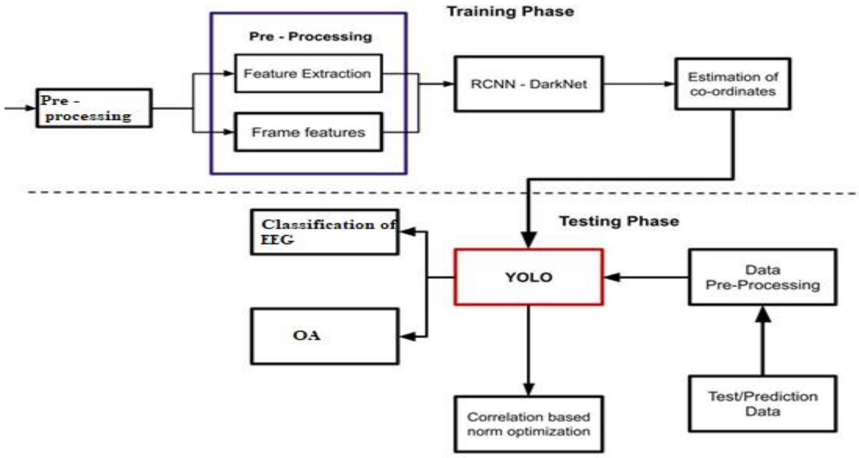


Fig. 1: Overall flow of FK_DARKNET

An EEG's frequency domain is represented in the time domain by a pre-processing block. Following blocks include breakdown of the EEG, noise removal using EEMD, and FEJER-KOROVKIN noise removal. Figure 2 presented the pre-processing involved in the FK_DARKNET for Schizophrenia classification is given.

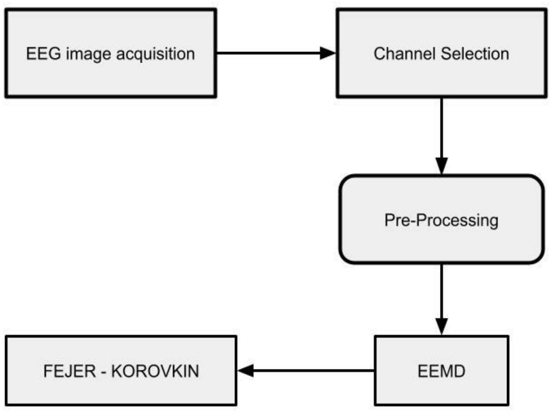


Fig. 2: Pre-processing architecture

To avoid mode mixing at different scales, a novel technique called Ensemble Empirical Mode Decomposition (EEMD) is applied to Ocular artifacts by treating the power spectral density of white noise as a uniform distribution function. EEMD retains EMD's benefit in non-stationary signal processing, and it can also successfully solve EMD's mode mixing problem. EMD (Empirical Mode Decomposition) is a time-space analytic method that is adaptive for processing series that are neither stationary nor linear. The method works well with non-linear and non-stationary signals like those found in nature.

The EEMD in the filtering uses biological aberrations, such as eye movements captured with electro oculograms to create intrinsic mode functions from the original EEG signal. These intrinsic mode functions are then combined using a simple threshold-based algorithm. EMD is an iterative technique for extracting IMFs, and that process is known as the sifting algorithm.

$$S(x) = rn(x) + ci + ci(x) \tag{1}$$

The IMF is ci when rn(x) is the residual of n extracted IMFs (x). There are two criteria for using IMF: (1) it must be a mono-component feature or a single instantaneous frequency oscillatory mode. Their zero-crossings are the same, as is the number of extremes that each have. (2) The average value for the upper and lower envelopes is zero. A sifting technique repeatedly removes IMFs from the signal to get a fraction that meets the aforementioned requirements.

3.1 Proposed Fk_Darknet Segmentation Of Oa Detection In Eeg

This section describes proposed FK_DARKNET for Schizophrenia detection from single EEG images with the removal of OA. Initially, the developed model FK_DARKNET for classification of the OA in the images of EEG through RCNN for classification of OA. In the next stage, identified components in the image are passed through the feature extraction stage with the classification of global entropy and local entropy. The developed model comprises the DARKNET model applied over the YOLO detector for classification. Finally, classification is performed in a deep learning network for the identification of Schizophrenia in the EEG signal.

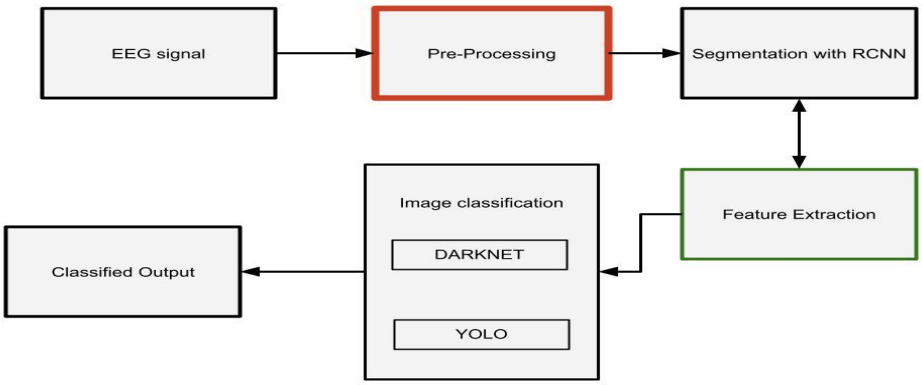


Fig. 3: Architecture of Proposed FK_DARKNET

The above figure 3 illustrated the overall architecture for classification and detection of Schizophrenia in the EEG signals. The estimation is based on the consideration of the EEG samples within the databases are pre-processed and segmented. After the EEG signal has been preprocessed, an estimate is calculated for the segmentation and categorization of the EEG signal for Schizophrenia, with OA removed. The model incorporates RCNN integrated with the YOLO architecture for the classification of the EEG signal. The normal form is estimated for computation and classification of Schizophrenia in the EEG signal for classification.

The proposed FK_DARKNET architecture comprises the EEG dataset with consideration of the OA in the EEG signal. The proposed FK_DARKNET model comprises the RCNN model integrated with the DARKNET with YOLO architecture model. As the YOLO architecture is involved in the estimation of the eight-layer architecture with convolutional layer architecture model with the size of 5 × 5 and 7 × 7 with fully connected layer model with max-pooling architecture. Figure 4 comprises the RCNN with YOLO architecture for the estimation of the model. In figure 5 applied RCNN model for signal segmentation and Schizophrenia, classification is presented.

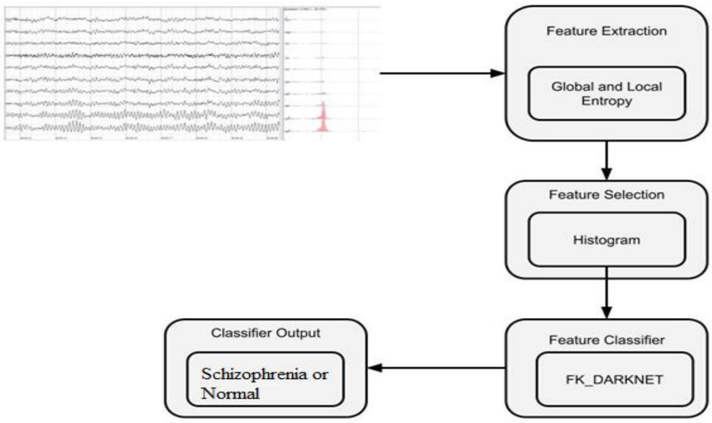


Fig. 4: Flow Chart of Proposed FK_DARKNET

In the above figure 4 overall processes in the proposed FK_DARKNET architecture for Schizophrenia and normal. Initially, the input EEG image is pre-processed to remove OA in the signal. In next stage, the entropy of the images is estimated for the classification of global and local values. Upon estimation, through histogram-based feature selection, YOLO will detect the signal, and classification is performed.

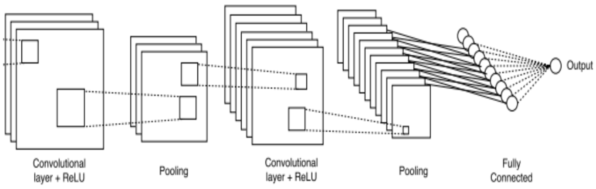


Fig. 5: Architecture of CNN

3.2 RCNN segmentation and YOLO clustering for FK_DARKNET

The proposed FK_DARKNET model incorporates RCNN with the YOLO model for classification and segmentation of Schizophrenia EEG signals. The FK_DARKNET comprises the DARKNET and YOLO model for clustering of the model in the image segmentation model. YOLO is involved in the clustering of the model for segmentation of the OA in the EEG signal. The architecture of the YOLO comprises the RCNN for reduction of the distance in the model objects with the estimation of the center of the cluster. The estimation of the YOLO architecture model is presented in equation (2) as follows:

$$F = \{F_1, F_2, \ldots\ldots, F_h, \ldots.., F_z\} \tag{2}$$

The image clustering in the EEG is based on consideration of the objective function F for the RCNN architecture model and it is denoted a in equation (3)

$$M_\mu = \sum_{i=1}^{q} \sum_{h=1}^{r} d_{ih}^{\mu} \times E_{ih} \tag{3}$$

Where, $E_{ih} = \|e_i - F_h\|$ explained as the center of the image cluter for estimation of the model as denoted in equation (4)

$$F_h = \frac{\sum_{i=1}^{u} d_{ih}^{\mu}.e_i}{\sum_{i=1}^{u} d_{ih}^{\mu}} \tag{4}$$

The constructed YOLO architecture for the image segmentation model as denoted in $Q_{u,v}^{FCM}$. In the proposed FK_DARKNET model segmentation of the model is estimated based on consideration of the DCNN. The image components of the RCNN comprise the conditions for the estimation of the images. The proposed FK_DARKNET model is involved in consideration of the equation (5)

$$Q_{u,v} = \begin{cases} Q_{u,v}^{A}; & if\ Q_{u,v}^{A} == Q_{u,v}^{FCM} \\ M; & if\ Q_{u,v}^{A} \neq Q_{u,v}^{FCM} \end{cases} \tag{5}$$

Where, $Q_{u,v}^{A}$ denoted as the RCNN segmentation output for the input EEG layer and YOLO model is represented as $Q_{u,v}^{FCM}$. Similarly, the term M is denoted as the RCNN criteria for the computation of the variables. Through the consideration of the model with RCNN in the YOLO model for estimation of the image pixels. The consideration of the RCNN model is involved in estimation of the YOLO segmentation model for computing the closeness of the image pixels. The RCNN value of the image pixels is computed as in equation (6):

$$M^{A} = MI\left(Q_{u,v}^{A}\right) \quad (6)$$

where, $MI\left(Q_{u,v}^{A}\right)$ denoted an image RCNN value for the consideration of the active contour model with the calculation of windows W_1, W_2. The computation of the model is based on the window size W_1 with dimensions of the 3 × 3, and the window size of W_2 is 4 × 4. The computation of the RCNN model for the computation of the OA in the EEG is stated as in equation (7)

$$MI(W_1, W_2) = E(W_1) + E(W_2) - E(W_1, W_2) \quad (7)$$

where, $E(W_1)$ denoted as the image entropy and window entropy as $E(W_2)$. The window joint entropy of the image is computed based on consideration of global and local entropy as in equation (8) and (9)

$$E(W_1) = -\sum_{u} pw_1(u)\, log\, p\, w_1(u) \quad (8)$$

$$E(W_1, W_2) = -\sum_{u,v} p_{w_1,w_2}(u, v)\, log\, p\, w_1 w_2(u, v) \quad (9)$$

where, $pw_1(u)$ denoted as the image conditional probability of the images. In similar manner, the estimation of the RCNN with the YOLO model architecture is represented as in equation (10)

$$M^{FCM} = MI\left(Q_{u,v}^{FCM}\right) \quad (10)$$

Segmentation value M is obtained by computing the RCNN model and estimating the entropy of the picture, as shown in equation (11).

$$M = \begin{cases} Q_{u,v}^{A}; & if\ Q_{u,v}^{A} == Q_{u,v}^{FCM} \\ Q_{u,v}^{FCM}; & \text{else} \end{cases} \quad (11)$$

The developed FK_DARKNET involved in estimation of the segmented image models for the computation for the FK_DARKNET as represented F = {F1,F2}.

3.3. FK_DARKNET for Histogram based segmentation in EEG

Image histogram involved in balance of the EEG images for identification and classification of the model. The computation is based on consideration of the global and local entropy for image pixel estimation. The image intensity of the pixels are computed based on the consideration of the distribution probability of the images and the distribution of the image is computed as in equation (12)

$$S_1^{k.c} = \left[D_G^{red} \quad D_G^{green} \quad D_G^{blue}\right] = D\left[Q_{u,v}^{R}\right] \quad (12)$$

In the above equation (12) κ ∈ {1, 2}, S[F _x0005_ u,v] represented as the segmented value of the image κ^th value of the images as represented in red, green and blue. The probabilities of the histogram is computed based on the geometric image features those are computed as FK_DARKNET. With consideration of the geometric features of the images in estimation of OA in the EEG images sequences. Generally, the geometric features of the images are computed based on mean, variance and standard deviations.

Mean: The image statistical features are computed for the images based on the estimation as denoted in the equation (13)

$$D_2^{k.c} = \eta = \frac{1}{p} \times \sum_{b=1}^{p} Q_{u,v}^{R.p} \quad (13)$$

where, P represented as the image dimensions with the size of (∃1 × ∃2) and F _x0005_,, the image count denoted as u,v for the j th image.

Variance: The image segmentation features are evaluated based on statistical information for the means values. The variance of the image is represented as in equation (14)

$$D_3^{k.c} = \frac{\sum_{b=1}^{p}\left(Q_{u,v}^{R.c} - \eta\right)}{P} \quad (14)$$

where, η indicates segmented mean value.

Standard Deviation: The variation in the image pixel are stated as Standard deviation those are accurately computed for the distributed values stated as in equation (15)

$$D_4^{k.R} = \sqrt{\frac{\sum_{b=1}^{p}\left(Q_{u,v}^{R.P} - \eta\right)^2}{P-1}} \quad (15)$$

The algorithm for the proposed FK_DARKNET model is presented as follows:

Algorithm 1: Proposed FK_DARKNET for Schizophrenia detection and classification

Begin

Select each element in image from C_o- 0; where the OA =1

Image $c \in C_o$, where, $\mu k(oA, c) > 0 - Q$

$Where Q = \phi$

do

remove image entropy c those included in the Q

$$fvalidation \leftarrow max_{d \in c_0}\left[min\left(f_0(s), \mu_k(S, d)\right)\right]$$

if $f_{val} > f_o(c)$ *then*

$f_o(c) \leftarrow f_{val}$

compute image entropy

$$\mu_k(d, e) > 0; f_{validation} > f_0(s) f_{validation} > f_0(f) \text{ and } \mu_k(d, s) > f_0(s)$$

End if

End while

end

Select image element histogram C_o- 0; where o =1

exaRCNNne o $- Q$

while $Q = \phi$

if $f_o(c)$ *remove noises in the image Q*

for image histogram $\mu_k(c, e) > 0$

do

$$f_{val} \leftarrow min\left(f_0(c), \mu_k(c, e)\right)$$

if

$f_{val} > f_0(e)$ *for* $f_0(e) \leftarrow f_{val}$

Estimate histogram on the element Q in every element e

End if

End for

End while

End

The classification of the Schizophrenia is based on the GLCM features of the image. Through the estimated image pixels EEG signal for OA removal is computed followed by the classification of the Schizophrenia and normal data.

4.Results And Discussion

The experimental outcomes for the proposed FK_DARKNET for OA eradication and Schizophrenia categorization are presented here. The experimental analysis consists of the EEG signal collected from the Kaggle datasets.

4.1 Experimental setup

The performance of the proposed FK_DARKNET model is implemented and tested in Python implementation software for experimentation in PC, 4GB RAM and I5 processor.

4.2 Database

The collected data of EEG signal is processed and examined with FK_DARKNET architecture for Kaggle data. The collected EEG data were processed and evaluated for the OA in the EEG signal image for removal.

4.3 Performance metrics

The evaluation of the proposed FK_DARKNET is examined based on consideration of different metrices such as Accuracy, TPR and TNR.

Accuracy: Accuracy of the model is evaluated with consideration of the classifier detection method as stated in equation (16)

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \quad (16)$$

TPR: The proposed FK_DARKNET involved in examination of the correctly or positive sample those are classified as stated in equation (17)

$$TRP = \frac{TP}{TN+FP} \quad (17)$$

TNR: The proposed FK_DARKNET involved in classified negative values for computation of the values as presented in the equation (18)

$$TNR = \frac{TN}{TN+FP} \quad (18)$$

Dice Coefficient: It offers the similarity level or coefficient for the spatial correlation between the segmented and ground truth value. The dice coefficient value of the image is computed as in equation (19)

$$DSC = \frac{2TP}{(FP+2TP+FN)} \quad (19)$$

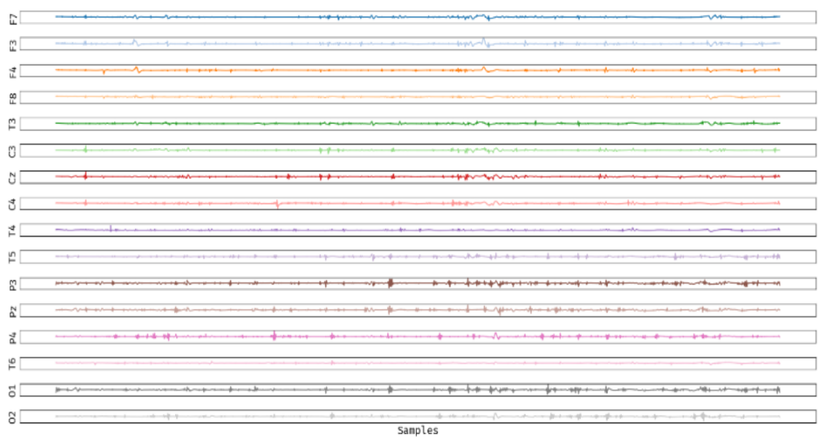
where (TP) stands for "true positive," (TN) for "true negative," (FN) for "false negative," and (FP) for "false positive."

4.4 Comparative Methods

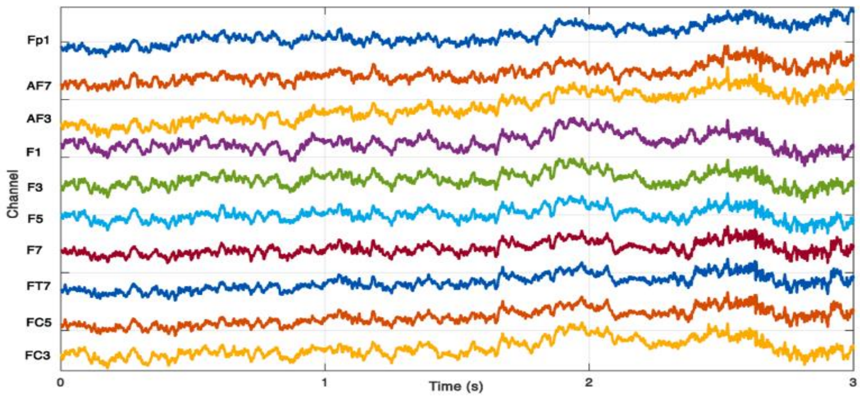
Results are compared to those obtained using state-of-the-art methods such NN[16], KNN[18], Random Forest[19], ACNN[20], SVM[17], Chrono-SCA_ACNN(Adopting segmentation and Chronological SCA in ACNN)[22], and DCNN[21]. Based on the consideration of above paper the performance is evaluated for the proposed FK_DARKNET.

4.5 Simulation Results

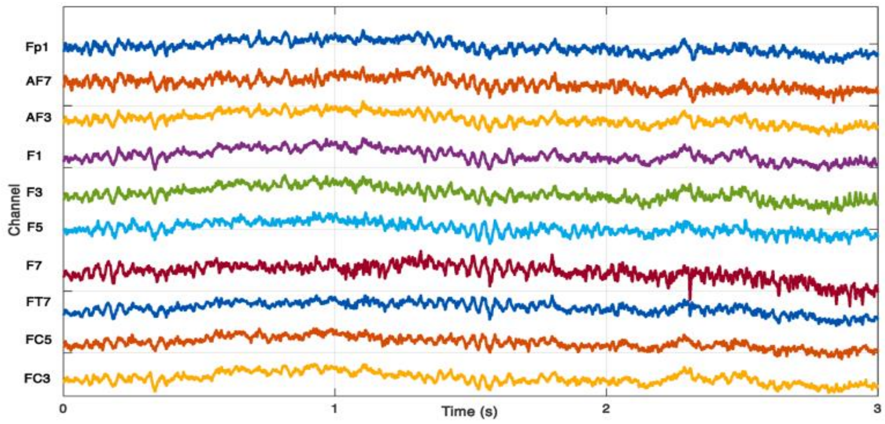
To classify and detect Schizophrenia in the EEG signal, the proposed FK_DARKNET uses the YOLO detector. The computation relies on omitting the image's border in order to maximize feature extraction. The histogram of the estimated image is used to calculate the feature values from which the estimate is made. The process involved in the EEG signal process for process is presented in figure 7. The computed signal for OA eliminated EEG signal and classification of the EEG signal are presented in terms of normal and Schizophrenia.



(a)



(b)



(c)

Fig. 7: Processed EEG Signal (a) OA removed EEG (b) Normal EEG (c) Schizophrenia EEG

The estimated EEG signal from the photos is used to evaluate and compute the data. In table 2 presented about the image processed for the developed FK_DARKNET model for the image.

Table 2: Feature Extraction before elimination of background pixel

Mean	**Standard Deviation**	**Smoothness**	**Skewness**	**Kurtosis**	**Entropy**
23.76	39.04	0.0253	1.568	2.897	3.676
12.007	43.68	0.0562	1.462	3.123	3.467
7.895	28.56	0.00534	1.156	3.696	2.7433
11.576	12.98	0.00657	2.572	4.258	3.2861
6.84	34.23	0.0134	1.957	5.736	2.278
9.868	16.78	0.0679	2.367	6.389	3.176
10.823	24.89	0.0316	1.693	12.906	2.471
11.795	27.98	0.0045	2.89	14.698	3.669

In table 2 observed that the visual characteristics pattern estimated for the evaluation of the intensity distribution of the image pixel in grey scale. The pixel intensity is estimated based on the distribution intensity with Haralick features. The evaluation is based on the grey level cooccurrence matrix (GLCM) of the grey level sub-images. The features of the images are computed based on the consideration of the 0, 45, 90 and 135^0. In table 3 segmentation time for the different pixel intensity levels are presented.

Table 3: Segmentation Time for FK_DARKNET

Dataset Image	Size(Pixels)	Time for Segmentation (sec)
1	150x220	9.56
2	240x210	11.45
3	220x290	10.73
4	145x230	7.3
5	240x470	13.26

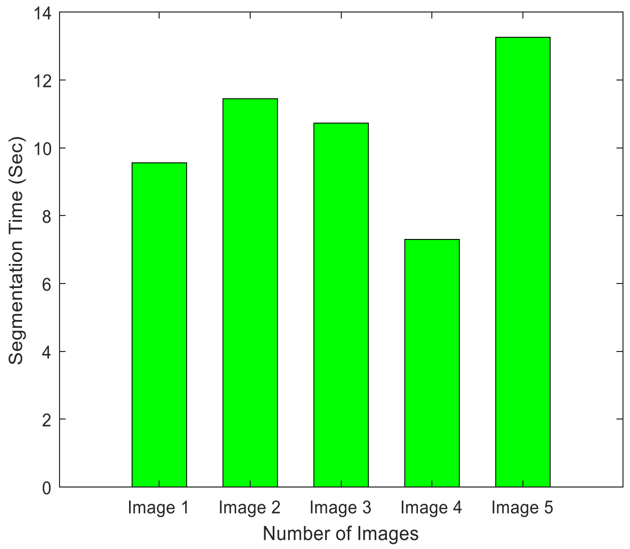


Fig. 8: Comparison of the Segmentation Time

In figure 8 presented the estimated segmentation time for the proposed FK_DARKNET model for the Schizophrenia detection and classification. The proposed FK_DARKNET involved in consideration of the segmentation time for the different datasets. The analysis of the proposed FK_DARKNET model is evaluated for estimation of the segmentation time. In table 4 estimated TPR values for the developed FK_DARKNET model is presented with existing technique.

Table 4: Comparative Study of TPR Validation Methods

K-fold	NN	SVM	KNN	Random Forest	ACNN	DCNN	Chrono-SCA DCNN	Proposed FK_DARKNET
4	61	62	64	69.4	72.7	78	82.6	86
5	63	65	69.7	74	79	80	87	89
6	66	72	76	78	83	84	85	89
7	69	75	80	84.6	86	87	88	90
8	75	79	81.6	84.2	88	88	89	91

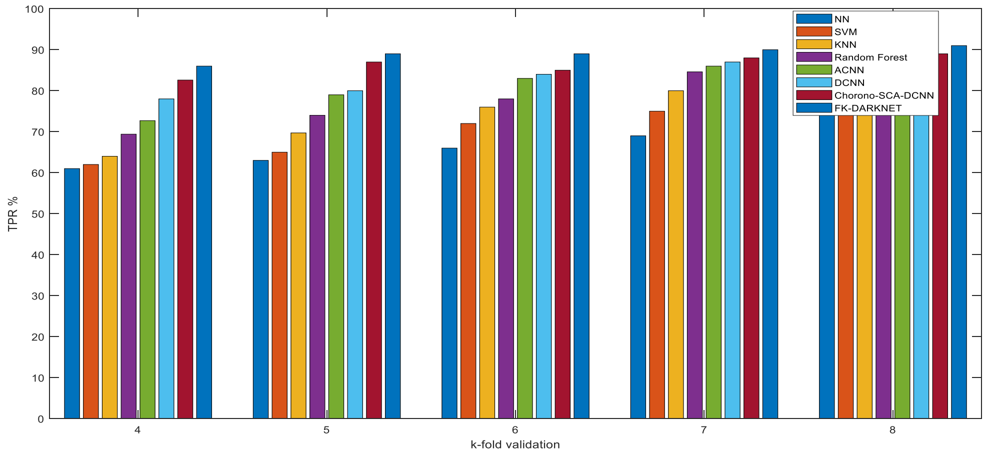


Fig. 9: Comparison of TPR

TPR value comparisons between the proposed FK_DARKNET and the baseline model show that the proposed classifier significantly outperforms the baseline classifiers in terms of performance. The estimated TPR value is ~ 4% higher than that of the conventional techniques. Similarly, in table 5 computation of the TNR value for the proposed FK_DARKNET model with existing classifier model is presented.

Table 5: Comparative Study of TNR Across Validation

K-fold	NN	SVM	KNN	Random Forest	ACNN	DCNN	Chrono-SCA-DCNN	Proposed FK_DARKNET
4	56.8	58	61.2	71.2	77	83	85	89
5	53	61.6	66	74	76	84	86	87
6	55.6	67.3	70	76	81	86	87	88
7	57.8	74.2	75	77	80.6	85.5	88	89
8	58.8	80	83	85	86	88	89	90.2

In figure 10 illustrated the comparative analysis of the proposed FK_DARKNET model is examined with the existing classifier.

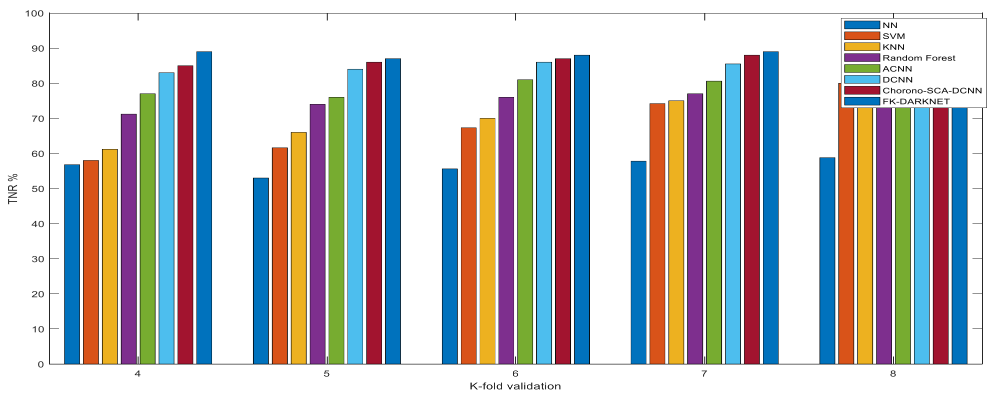


Fig. 10: Comparison of TNR

Predicted gains in TNR when implementing the proposed FK_DARKNET. When compared to the status quo method, the proposed model's performance is found to be significantly better. In table 6 the proposed FK_DARKNET model performance is comparatively examined for accuracy.

Table 6: Analysis of Accuracy for different validation

K-fold	NN	SVM	KNN	Random Forest	ACNN	DCNN	Chrono SCA-DCNN	Proposed FK_DARKNET
4	45	49	53	62	69	71	74	79
5	52.34	56.2	61	65.7	71.34	73.65	77.26	80
6	64.2	66	63.60	68.5	74.63	81.26	82	84.6
7	65	69	67.29	70.83	78.49	88	83	89
8	69	70	71.2	73.6	81.1	86.3	85	90.6

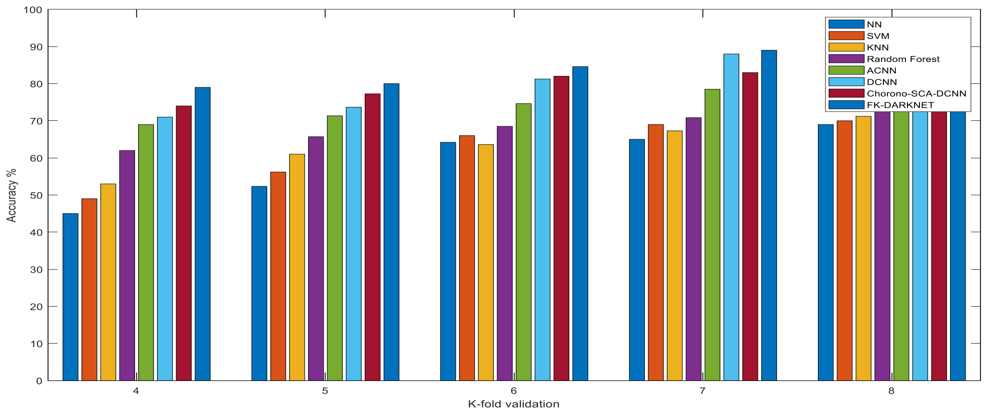


Fig. 11: Comparison of Accuracy

Figure 11 compares the proposed FK_DARKNET model's accuracy to that of other popular deep learning architectures. In contrast to the preexisting classifiers, the proposed model was found to have a higher accuracy value in the comparative study. The accuracy model is ~5% higher accuracy than the conventional techniques. In table 7 overall comparison of the proposed FK_DARKNET with existing classifier is presented.

Table 7: Overall Comparative Analysis for Schizophrenia classification

Methods	**Dice Coefficient**	**TNR %**	**TPR %**	**Accuracy%**
Chrono-SCA-DCNN	83.56	87	86.3	80.25
SVM	79.45	68.22	70.6	62.04
KNN	81.34	71.04	74.2	63.2
Random Forest	83.56	76.64	78.04	68.12
DCNN	84.92	85.3	83.4	80
NN	77.67	56.4	66.8	59.1
ACNN	82.56	80.12	81.7	74.9
Proposed FK_DARKNET	86.57	88.6	89	84.64

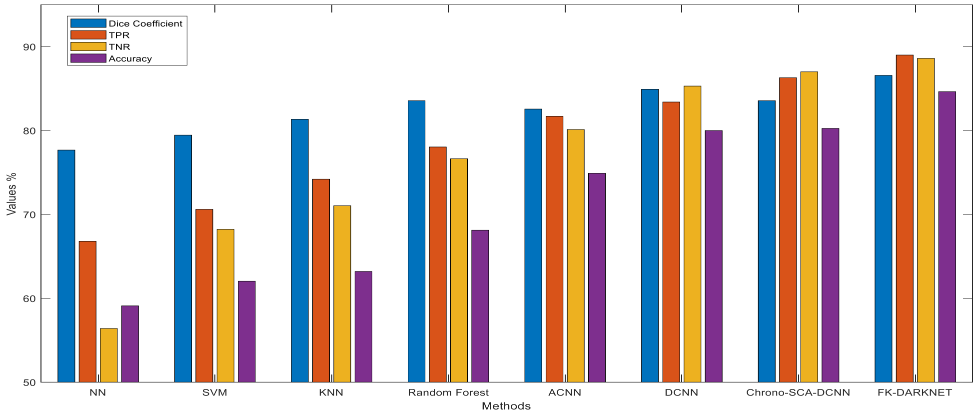


Fig. 12: Overall Comparison

In figure 12 presented the comparative analysis of the proposed FK_DARKNET model for existing model. According to the results of the comparison, the proposed FK_DARKNET model provides an increase in TPR, TNR, and accuracy over the baseline classifier.

5.Conclusion

This paper concentrated on the Schizophrenia detection and classification in the EEG signal for processing of the EEG signal with removal of OA. The proposed FK_DARKNET architecture uses the fejer-korovkin pre-processing model for elimination of OA in the signal. The developed model comprises of the two stages such as entropy estimation and histogram normalization for feature extraction and classification. Through RCNN model segmentation is performed in the EEG signal image for processing. The analysis expressed that the with the proposed FK_DARKNET model overall performance of the EEG signal for Schizophrenia classification is increased compared with the conventional technique. As the findings show, the suggested FK_DARKNET outperforms conventional classification methods in terms of TPR, TNR, and accuracy.

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