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# ECG Biometric for Human Authentication using Hybrid Method

**Keshavamurthy T G[1], Eshwarappa M N[2]**
[1]Assistant Professor, Department of E & C
Sri Siddhartha Institute of Technology
Karnataka, India
keshavamurthytg5@gmail.com
[2]Professor, Department of E & C
Sri Siddhartha Institute of Technology
Karnataka, India
eshwarappamn@ssit.edu.in

**Abstract**—Recently there is more usage of deep learning in biometrics. Electrocardiogram (ECG) for person authentication is not the exception. However the performance of the deep learning networks purely relay on the datasets and trainings, In this work we propose a fusion of pretrained Convolutional Neural Networks (CNN) such as Googlenet with SVM for person authentication using there ECG as biometric. The one dimensional ECG signals are filtered and converted into a standard size with suitable format before it is used to train the networks. An evaluation of performances shows the good results with the pre-trained network that is Googlenet. The accuracy results reveal that the proposed fusion method outperforms with an average accuracy of 95.0%.

**Keywords**-Google Net, Convolutional Neural Network, Fusion, Electrocardiogram.

## I. Introduction

To enhance the convenience, safety, inclusion in society and to give a potential use in several industrial and research areas, Noticeable biometric traits that have been clearly utilized in practical uses involving fingerprint, face and iris. Additionally, the novel improvements of AI methodologies form them vulnerable to spoofing attacks along their inherit weakness. In [1]-[4] a general spoofing attack on finger prints or face was explored and evaluated. To combat over the illegitimate user access and presentation attack to the systems, continuous biometric authentication technologies, aliveness identification or spontaneous biometric authentication should be considered [5]-[7]. Spontaneous biometric authentication spontaneously verifies the detection of the user by utilizing non-invasive evaluable sensor that can collect user's biometric data. Hence spontaneous biometric authentication is taken as real methodology of the recent generation due to different characteristics of the ECG signals this is highly effective methodology for the spontaneous biometric authentication. The ECG signal nature is easy to utilize, ubiquitous and difficult to counterfeit, to access privilege for users to identify particular person, for spontaneous authentication.

ECG-based technique is normally used [8]. Moreover, many apps involved with a spontaneous monitor for utilizers ECG and derive quantitative evaluations of existing stress condition, fatigue, and enabling user to know exact disease condition, [9,10]. Electrocardiogram can be captured for health applications and are also utilized for biometric authentication, enabling the development of wearable technology like Apple watches. ECG signals are also recorded to track the health of our users.

The ECG immaturity improvements are caused by a lack of genuine ECG data. The research community also relies heavily on a small ECG gallery, which leads to good performance but high error rates. In order to balance various crucial evaluation metrics, such as the false acceptance rate, false reject rate, and equal error rate, the majority of existing systems typically fail to provide standard metrics for assessing ECG data assessment outcomes. The essential steps in creating the optimal algorithm for each application, filtering, segmentation, feature extraction, and matching, have not even been extensively examined by the majority of methodologies. The Figure 1 shows the ECG personal authentication system.

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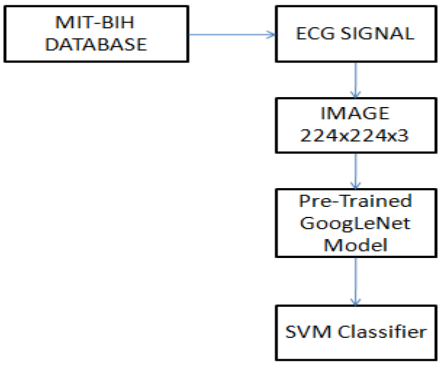


Figure 1. Deep learning-based conventional personal authentication system that uses ECG

Figure 1 shows the traditional personal authentication system that combines deep learning with an ECG. A personal ECG database that includes all ECG signal kinds that depend on the individual state, such as running, sleeping, eating, calmness, etc. is initially required. SVM classifier performs an authentication by using deep learning in conjunction with the user's personal ECG database.

ECG signal gives information about the human heart, generally evaluated by an electrocardiograph. The various sensor placement combinations give little changes which enables improved particular portion of the waveform. 12 leads are the general usage of the health, which are categorized as chest and limb leads. All these evaluations consist normal behavior as recurrent and as periodic patterns [11]. The QRS complex, which is made up of the waveforms Q, R, and S, is the most important part of the ECG. As it is covered by P and T waves, as shown in figure 2, it is typically elaborated to P-QRS-T.

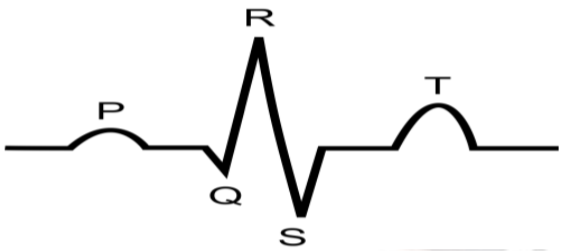


Figure 2. Normal Sinus Rhythm waveform and some of its relevant points

By creating the individual identification these signals are appear in inter-individual variability [12]. Additionally, it is confirmed that day-by-day variability and long-term in addition, it has been proven that the long-term intra-individual variability are comparable [13], enabling the comparison among various periods, also considering confirmation with more than a year of separation [14]. Additionally, from each and every life being ECG can be obtained which gives life proof identification. The signals from the ECG are involuntary, real its function cannot be cannot be accessed in easy way these signals which are representing the action of the organ. ECG is more popular and highly significant with these features in the field of biometrics and many studies have been under taken since before 2000s [15].

Background on ECG: - An electrocardiograph, also referred to as an ECG, is a device that visually displays the heart's activity and allows users to identify it. ECG can be viewed as a mixture of different action potentials produced at specific times by the atrio ventricular (AV) and Sino atrial (SA) nodes. The PQRST complex of letter waves on the ECG is the major method of identification according to Figure 1. The P wave, which is very brief and lasts 0.08 seconds represents the depolarization migration from the SA node along the atria node. The ventricular depolarization results in a large QRS complex, which continues ventricular contraction. The T wave, which represents ventricular repolarization, lasts for 0.16 seconds. ECG waveforms might vary for each person according on their torso conductive characteristics, heart position in the chest, shape, and size. The two recording options for the ECG signal are off-the-person and on-the-person. On-the-person recording refers to direct evaluations using body sensors that must be affixed to the patient's body and typically require conductive paste or gel. This method is mostly used in a medical equipment near the chest to obtain an ECG signal. Also, this technology is often used in the medical area as a diagnostic tool where the way of capture is very controlled. For instance, ranges of the devices are from bedside monitors to attachable monitors for heart rate monitoring. Additionally, ECG signals applicability can be obtained in an on-the–person technique is representing the main biometric research. The subjects feel a great deal of intrusion with this method. ECG signals can be accessed via "off-the-person" recording; therefore, subject pretreatment with surfaces is not essential. For instance, the range of these devices includes wearable electronics with dry electrodes. The key benefit of this technology is that the user does not need to be involved in the positioning of the sensors. The prospective industrial applications of ECG-dependent biometrics are nicely arranged with these novel approaches. As a result, the "on-the-person" datasets that make up this type of ECG database are very variable and noisy.

## II. LITERATURE REVIEW

Non-fiducial-based, hybrid based, and fiducial-based techniques are the 3 major classifications of the ECG biometric literature. Few original signal representations are utilized instead of its morphological features in non-fiducial approaches. ECG signal fiducial point's characteristics are utilized as a feature. And at last, hybrid-based techniques uses both non-fiducial and fiducial characteristics. Using fiducial approaches, it is possible to retrieve all or some of the temporal ECG feature points. The area, angle, and amplitude of the fiducial wave points make up all of these characteristics [22], and [23]. ECG dependent

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biometric system is developed by Irvine et al. [16] to analyze the mental and emotional conditional changes upon the detection action. Here which are undergone with two practical works every work contains various task that denotes the several mental and emotional conditions. The temporal ECG signal provides 15 fiducial points, including the L'P', S'T', and QT intervals. Features quantity can be minimized by a stepwise discriminant estimation conduction. Later, a linear discriminant classifier was utilized as portion of the detection level. The outcomes which are represented that the ECG can be utilized in the biometric procedures. The method with Bayes classifier is utilized to detect the subjects this is performed its work upon the same database to analyze the requirement of minimum heart beat for the verification of the person [24] and to analyze the emotional condition effect.[25] This technique was introduced by Zhang and Wei [26] The features of fudicial consisting of ECG feature points like duration, amplitude and PR and QRS fiducial intervals. Distinctive practical works done on ECG leads. Such as 79% of the accuracy is obtained "Lead V2", 85.5% of accuracy is obtained from the" Lead I" Moreover ECG fiducial characteristics are studies by the Venkatesh et al. [18] to recognize the 15 subjects.

Fiducial points were first located, and then a collection of fiducial features including the ST, QRS, and PR intervals were extracted. Several classifiers, including one-stage and two-stage classifiers with Fisher's linear discriminant and dynamic time-wrapping analysis with KNN, were used for the detection and 94% of average accuracy was obtained. The primary function of these technologies is the extraction of fiducial points, which requires an algorithm that is resistant to noise that can alter these points. Additionally, electrode insertion and an ECG device are used to measure the amplitude of the fiducial point. Therefore, electrode- and heart-rate-independent feature technologies are used before the fiducial-dependent technique. To acquire the features, it is not required to use all of the fiducial ECG points in the non-fiducial features.. For the segmentation of the heart beat one or more fiducial points can be utilized. Generally, from the frequency domain extracted features are obtained. This technique gives a yields good approach even the T and P features are affected by person's health condition or a noise [17],[27], [51]. For instance, Fatemian et al. discovered the Q, R, S, and T wave points. Every subject's heartbeat is then sorted, and the median of numerous beats is used as the subject's gallery. On the tested dataset, accuracy of 99.62% is achieved. Hejazi et al. [29] discuss the use of the ECG signal for individual verification. 52 healthy ECG readings are taken during the cohort's 3-minute ECG recordings. ECG signals are initially preprocessed to remove noise. The signals from each participant are thereafter divided into non-overlapping windows that are spaced out every five seconds. The normalized autocorrelation coefficients, which total 1028 coefficients, are then determined for each window. Along with the SVM classifier, non-linear and linear feature reduction algorithms were used. Camara et al. [30] looked at few previous publications that investigated the extraction of characteristics through signal manipulation.

Some studies have involved with deep learning techniques with ECG biometrics. Like, in heart ID detection method 1-D CNN is utilized which was discussed by Zhang et al. [20]. Blind segmentation and the elimination of noise in ECG signal is performed. The wavelet transform is performed to the segments to finally get the autocorrelation coefficients. 93.5% of the average rate and detection rate are acquired by combining different wavelet elements. Da Silva Luz et al. [21] employ the fusion of the original ECG heartbeat to identify the patients. To assess the distance between the probe and gallery sets, they used two CNN networks, one for spectral images and the other for raw data. Evaluation of similarity check is obtained by applying the fusion rule upon at score level. A 1D CNN is also provided by Labati et al. [32] who use the ECG signals of healthy people to remove noise and extract QRS complexes by selecting 8 complexes at 4 seconds. To talk about the 1D CNN Raw ECG data from 18 and 90 healthy participants were used by Wieclawet al. and Page et al. [33], who first filtered the signals before obtaining the QRS complexes. Zhanget al. [34] uses the raw ECG signal to obtain the 2D representation by incorporating the lagged signal version. There were just 10 individuals used in that study. The hybrid-dependent features in the biometric system combine both fiducial and non-fiducial aspects. Wang et al.'s [35] ECG detection method makes use of both non-fiducial and fiducial characteristics. The fiducial characteristics make use of the amplitude and placements of the P, Q, R, S, and T points. For the non-fiducial features, discrete cosine transform and autocorrelation coefficients are used. In this study, we estimate that a change in the biometric ECG systems' ECG duration is required for detection. Therefore, we argue that these methods reduce complexity and provide innovative models and features that can increase the biometric system's rate of detection.

## III. CONVOLUTIONAL NEURAL NETWORKS

The CNN architecture differs from the normal neural network architecture. Each CNN layer's 3D-organized neurons, which are arranged in depth, breadth, and height, convert a 3D input volume into a 3D output volume of neuron activations. In the CNN architecture, there are three different sorts of layers: pooling, convolutional, and completely. There is no requirement that all of the neurons in the subsequent layer connect to those in the preceding layer. Pooling and convolution procedures were applied in sequences to the input data using a filter to produce a feature map. The output of the convolution layer is considered

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to be these merged feature maps. The Convolutional layer constantly generates the time-consuming CNN training while enabling the necessary CNN block. Convolution is used in this case to compute the output of the neurons using the input. The shared weights sets, which are made up of small receptive fields, are the convolutional layer parameters. In pooling layers, non-linear down sampling procedures are used. The most important nonlinear operation is max pooling. The output is categorized as a group of all the maximum, non-overlapping frames for each group's input. In this way, max-pooling layers reduce the likelihood of over fitting, the complexity of the computational network, and the number of parameters. Max pooling layer is consequently positioned between the convolutional layers. In order to reduce the risk of overfitting, dropout layers are frequently added. Connections with particular probability and dropping neurons in the CNN are the two major roles of the dropout layer. The activation function is a non-saturating ReLU (rectified linear unit). These function as classifiers with all neurons in a layer that is fully linked. As a result, which causes overfitting, it is necessary to train the CNN from scratch, which requires the greatest amount of training data. The fine-tuned pre-trained CNN that will be used in this study is described in section 4.2. CNN was implemented using Google Net [43] and Alex Net [44].

## IV. PRETRAINED NETWORKS

A pre-trained network has pre-trained weights that can be used in a related piece of work. According to Chen et al., the use of CNNs in domains is constrained by the quantity of the dataset, but the problem can be solved by using pre-trained data [36]. Additionally, CNN training from scratch demands a lot of time and memory, as well as the highest level of computer capability. Pre-trained CNN can be used to increase accuracy when the dataset is small [37–38]. According to Yosinski et al. [38], distant at sk weights perform better than randomly initialized weights. The pre-trained CNNs that are mentioned in the literature are ResNet, GoogleLeNet, VGGNet, and AlexNet. Therefore, AlexNet and GoogleLeNet are frequently used and produce superior results for feature extraction and classification. instance, GoogLeNet and AlexNet have been used in data analysis along with anatomical applications [39], computed tomography [40], and biomedical signal processing [41,42], for example, interstitial lung disease. They have also been used in the identification of malaria-infected cells, with GoogLeNet and AlexNet achieving 98.13% and 95.79% accuracy, respectively. 91.66% of accuracy is achieved by SVM machine learning tool. Current research works upon the best configuration of the 2 broadly utilized CNNs for the purpose of classification and detection of ulcer. By freezing the first layer weights is during the training of the system frozen layer weights were not adjusted. Each and every weight in the fully connected layer, which is used for mapping feature representations, is trained using the stochastic gradient descent (SGD) algorithm and is initially set to random values.

Support Vector Machine (SVM): Electrocardiogram (ECG) categorization often uses the machine learning algorithm known as Support Vector Machine (SVM). The automated classification of ECG signals has emerged as a significant study subject in recent years. The ECG is a frequently used clinical tool for the detection of cardiac disorders. The foundation of the supervised learning algorithm SVM is the discovery of a hyperplane in a high-dimensional space that divides two classes of data. The positive and negative samples, which are represented as points in the feature space, are maximally separated from one another by the hyperplane found by the SVM method. SVM has proven to be quite successful at handling classification issues with a limited number of training data.
The two primary processes in ECG classification using SVM are feature extraction and classification. The process of turning the ECG signal into a collection of features that may be utilized for classification is known as feature extraction. These characteristics may be morphological (like the length and amplitude of the QRS complex) or statistical (like the mean and standard deviation). SVM is used to categories the ECG signal into several groups, such as normal, arrhythmia, or ischemia, after the features have been extracted. SVM has been demonstrated to be very efficient in classifying ECGs, obtaining excellent accuracy rates with little training datasets. The application of SVM in ECG classification has the potential to increase the precision and efficiency of diagnosis and may result in more effective cardiac disease therapy and management.

GoogLeNet: GoogLeNet is regarded as the champion of the 2014 ImageNet Large-scale Visual Recognition Challenge (ILSVRC), an annual competition that assesses advancements in object categorization and identification [43]. The GooLeNet achieves 6.7% of the error rate when used with inception modules. Figure 3 illustrates the initialization modules used to build the network.

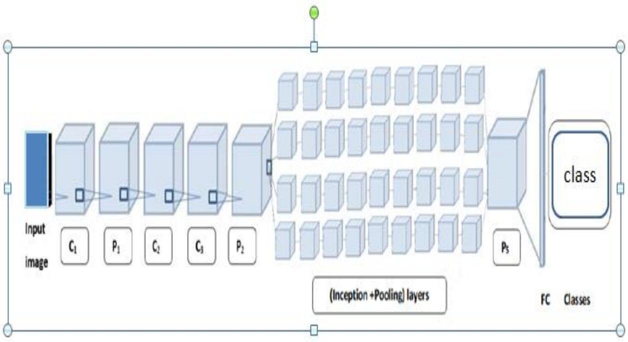


Figure 3. Architecture of the GoogLeNet

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Convolution layers are represented by Ci, Pooling layers are represented by Pi and fully connected layers are represented by FCi.

## V. PROPOSED METHODOLOGY

Figure 4 depicts the block diagram of the proposed approach. It consists of pre trained CNN network such as Googlenet and also a fusion of googlenet with SVM classifier for the performance evaluation of ECG signal classification for person authentication.

In the proposed methodology the steps as follows:

- ECG signals are collected from database.
- ECG signals are filtered to remove high frequency noises - The signal preprocessing is done for removing the noise that is present in the gathered signals. Here, the preprocessing of the input signals is done by the LPF technique. An LPF represents a filter that passes signals using a frequency lesser than a chosen cut-off frequency and attenuates signals having frequencies more than the cut-off frequency.
- All one-dimensional ECG signals with 40000 sample values are converted and reshaped of size 224*224*3 Image. Sample of ECG Signal to Image .jpeg Format shown in figure 7.
- The layers of googlenet are concatenated with SVM classifier except the first and the last three layers.

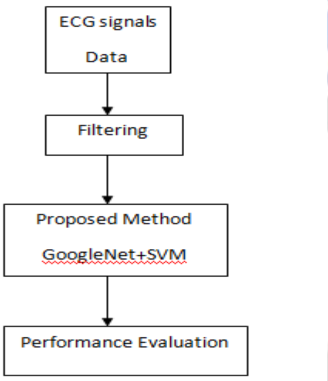


Figure 4: Proposed Flow Diagram

The accuracy results reveal that the proposed fusion method outperforms with an average accuracy of 95.0% as compared with the individual performance of googlenet for the same dataset.

## VI. RESULTS AND DISCUSSION

GoogleNet network are trained using MATLAB with a GPU system with the following specifications. Processor: Intel ® Core™ i7CPU and Graphics Card: NVIDIA GeForce. Various parameters are considered to evaluate the performance of GoogleNet with SVM. The figure 5 shows the sample of the ECG signal and after denoising ECG signal shown in figure 6. The figure 7 & 8 shows the entire simulation process that is confusion matrix of our proposed method obtained and observed. The overall performance analysis for the proposed method for the gathered dataset is displayed in Table I. Table I, presents the mathematical values obtained with the proposed fusion method. The accuracy of the proposed method is 95.0% giving good results l. The F1 Score, FNR, sensitivity and precision also progressed. Therefore, the performance analysis holds better outcomes with the hybrid method for person identification. The experiments were performed with the following dataset - https://physionet.org/content/ecgiddb/1.0.0/. It is composed of 310 ECG recordings that are being attained from 90 persons. Each recording is composed of information regarding recording date, gender, and age, 10 annotated beats, and ECG lead 1.

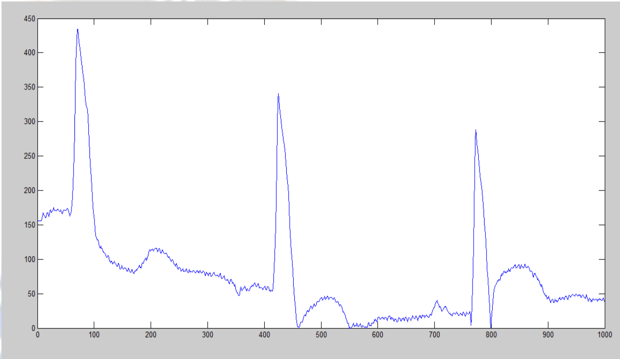

Figure 5: The sample of the ECG signal

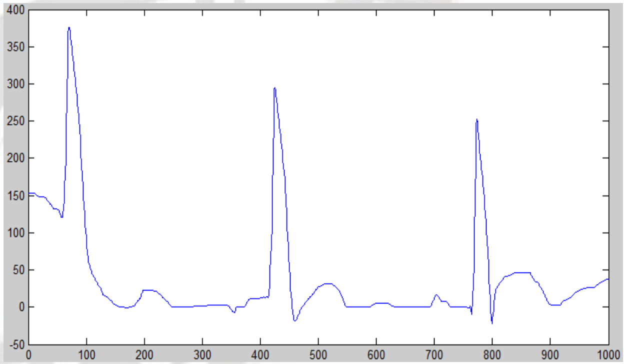

Figure 6: Denoised ECG Signal

Figure 7: ECG Signal to Image .jpeg Format

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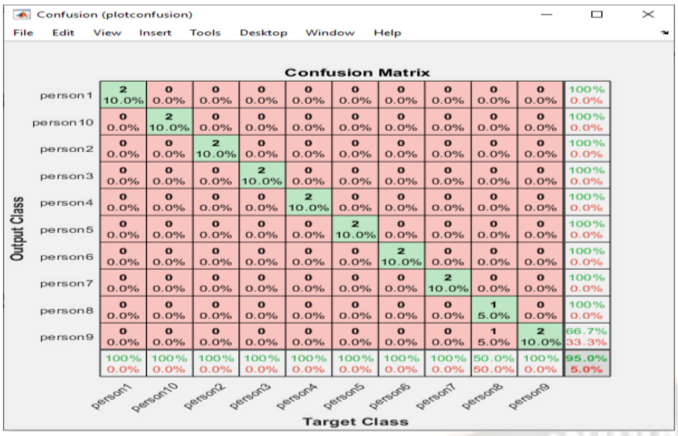

Figure-8: Confusion Matrix of Proposed

| Performance Measures | Proposed Method |
|---|---|
| Sensitivity | 0.98628 |
| FNR | 0.01372 |
| F1 Score | 0.9859 |
| Precision | 0.98553 |
| FDR | 0.014471 |
| Accuracy | 0.95 |
| Specificity | 0.5 |
| FPR | 0.5 |

Table 1: Overall performance analysis for the state-of-the-art hybrid machine learning and deep learning based algorithms-based person identification

## CONCLUSION

Convolutional neural networks are used here to classify the ECG data for human authentication for biometric applications. The table in results summarizes the performance in terms of accuracy of the proposed fusion approach. However, the results are more promising as compared with traditional machine learning approaches. CNN's automatically extract features which results in classification by using SVM. The accuracy results reveal that the proposed fusion method outperforms with an average accuracy of 95.0% as compared with the individual performances of alexnet and googlenet for the same dataset

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