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A MULTIPLE SYSTEM BIOMETRIC SYSTEM BASED ON ECG DATA

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Abstract- The subject matter of this article is an analysis and design of a biometric system based on deep learning and machine learning for human identification through electrocardiography (ECG). The goal Building a biometric system to identify people and create simulated data for human identification through electrocardiography. The tasks solve the problem of the lack of a data set dedicated to the security issue in the field of ECG by relying on a global data set that has been worked on in a new way by previous researchers and improving on this method, and by creating a new data set dedicated to the security issue through the use of pre-processing operations and extraction and selection best feature process. Additionally, the tasks solve the problem of providing additional prints as a backup copy due to a pc failure. The methods used are: The first model supports deep learning technology using a single neural network (CNN) algorithm. In contrast, the second model supports machine learning (ML) technology through several neural network algorithms (the SVM algorithm). Moreover, the use of a global dataset (Physikalisch-Technische Bundesanstalt (PTB)) and the two models participate in one processing process, the purpose of which is to create new data dedicated to security and the use of two different data division techniques, which are hold-out for deep learning and k-fold for machine learning, and confusion matrix to evaluate the results. Test data. Results were obtained: The results obtained for the PTB dataset for the DL model (Accuracy: 99.4%, precision: 99.9%, recall: 99.5%, F1-score: 99.7%) and the results of the ML model (Accuracy: 98.1%, precision: 99.7%, recall: 98.3%, F1-score: 99%) Conclusions: Biometric systems must provide data that is provided with backup copies for one person in order to work on them in the event of an error. The ECG data lacks this, as it is intended for diagnosing heart diseases only. The use of processing operations about the ECG plays an essential role in constructing the data.

Keywords: SVM Algorithm, ECG Data, Machine Learning, Noise.

1. INTRODUCTION

Everyone is concerned about their data security due to the rapid advancement of artificial intelligence technology. Individuals' unique data must often be a "key" to their personal information [1].

Therefore, the significance of biometric systems, which use mathematical algorithms and biometric data to identify a specific attribute of an individual, has increased [2]. There are a variety of uses for biometric systems, such as fingerprints, face scans, and iris scans. Palm print and ECG are the most commonly employed human identification technologies [3]. An electrocardiogram (ECG) is a physiological signal that records heart activity over time (ECG).

It is used in two fields, one to detect heart diseases and the other in biometric security systems to identify human identity [4]. *P* waves, *QRS* complexes, and *T* waves may differ between different ECGs, yet they are all connected. However, the difficulty may vary depending on age, race, height, weight, and lifestyle [5, 6]. Higher QRS compounds for athletes are attributed to a more muscular left ventricle. Also, these cardiograms are not the same among humans, as they contain individual features in each person. As a result of these features, heart fingerprint systems have recently been adopted and have become fertile ground for researchers to delve into them [7, 8]. This paper provides an idea of the work of the ECG system to identify people based on learning methods.

2. NOISE

The bulk of the time, ECG data that has been recorded has noise. In most cases, the noise will degrade the signal and reduce the precision of feature extraction and classification [5]. During acquisition and transmission, many disturbances affect the ECG signal. The ECG signal predominantly contains two types of noise. High-frequency noises include electromyogram noise, additive white Gaussian noise, and power line interference. Low-frequency sounds feature a meandering baseline. Noise contamination of the ECG signal may lead to a faulty interpretation. Numerous denoising techniques are available [9]. Table 1 displays ECG noise.

3. ECG BIOMETRIC SYSTEM

The system employs pattern recognition to compare individual feature points to a database template, thereby establishing the reliability of the biometric information. Depending on the context, biometric systems can be used for either verification or identification. Biometric validation and identification rely on exact matches between a biometric trait and a database registration.

Table 1. Noised of ECG [10, 11]

NO	Noise name	Description
1	Power line interference	50/60Hz pickup and harmonics. Electromagnetic interference from power lines, electromagnetic fields from neighboring machines, Stray alternating current fields due to cable loops, improper patient or ECG machine grounding, and electrical appliances create 50 Hz signals in ECG machine input circuits
2	Electromyogram (EMG) Noise	Muscle electrical activity generates EMG noise. EMG is 10 kHz. Surface EMG can contaminate ECG sections, causing data processing and analysis issues
3	Baseline Wander	ECG noise with a low frequency is known as baseline drift. This is due to the effects of breathing and moving. The drift in the baseline is more significant than 1Hz. The difficulty is caused by baseline drift, which makes peak identification and analysis difficult
4	Channel Noise	ECG signal transmission causes channel noise. Poor waterway conditions. It is primarily white Gaussian noise with all frequencies
5	Electrode Contact Noise	Electrode contact noise occurs when the electrode loses contact with the skin, disconnecting the measuring device from the subject
6	Motion Artifacts	Motion artifacts are transient alterations to the baseline caused by differences in the impedance between the electrodes and the skin. The ECG amplifier can identify a new source impedance whenever this impedance changes since this impedance produces a voltage division with the amplifier input impedance. The source impedance has a direct bearing on the input voltage of the amplifier

If neither change, the visitor is not who they claim to be, and they should be turned away [3]. Evidence suggests that the database identification code must be unique when verifying data. The biometric data must match, unlike the password verification method. Every visitor's detail must be put into the master database [5]. In the verification mode, a user's biometric information is compared to a stored template to determine whether or not they are who they claim to be. The real-time feature is compared to each biometric pattern individually, and the process is repeated until a single, distinguishable pattern emerges. To ensure public safety, the identification mode seeks out biometric features that correspond to the acquired template data [6].

After a user sign up for the first time, an enrollment template is created and saved in the system. A novel presentation template is generated each time a new user attempts to log in. After acquiring biometric signals, signal processing techniques are employed to transform the signals into reference templates, which can be utilized later to authenticate the individual's identity. Various procedures may be necessary, such as identifying artifacts, filtering signals, segmenting data, normalizing amplitudes and temporal characteristics, detecting outliers, and extracting features. In this context, feature extraction has the potential to yield fiducial, non-fiducial, or hybrid features [10]. Biometric algorithms compare the features derived from the presentation template with the features from the stored enrollment template to determine the probability that they belong to the same person [7].

For example, the Technique may be used for either authentication or identification, which is helpful. Proof of identity is required for authentication. The obtained biometric information is compared to the data linked with the claimed identity in the system's memory. When identifying, a biometric system will compare the collected biometric information to its database to determine whether or not the individual matches any of the stored profiles. In this way of identification, the user is not even required to assert their identity [8].

4. RELATED WORK

In R. Boostani, et al. (2018) [12], A biometric system for dependent identification that extracts instantaneous frequency, phase, amplitude, and entropy from EKG data using empirical decomposition (EMD) and, as a final stage, classifies individual features from KNN. EMD divides the raw ECG signals into intrinsic ECG validation modes. Application of the Hilbert transform to the last EMD component produced a low-frequency analytic signal with *P* and *T* waves. The parameters of the analytical signal included instantaneous frequency, phase, amplitude, and entropy. Due to the added noise in autocorrelation and covariance, the correlation-based method and the AR model had low validation rates.

Wavelet features, credit score, and PCA features have a high validation rate but generate too many features, which makes the callback phase too long for online use. Zhang, et al. (2019) [13], Person recognition uses a deep convolutional neural network that extracts the unique properties of the electrocardiogram. It extracts unique features from the ECG segment without reference points, circumventing the complex signal feature point extraction process. Use a feature map and standard deviation for global classification and simplify the simple voting method.

In S. AlDuwaile and M. Saiful Islam (2021) [14] A biometric system utilizing deep learning has been proposed to analyze a truncated segment of the electrocardiogram (ECG) signal for the purpose of identifying individuals' vital measurements. By leveraging the entropy augmentation of a brief segment of the cardiac signal, a compact convolutional neural network (CNN) is developed to achieve enhanced generalization capabilities. Experiments were performed on two databases, including single and multiple session inputs. In addition, the performance of the proposed classifier was compared to four known CNN models: GoogleNet, ResNet, MobileNet, and EfficientNet.

In A. Hammad, et al. (2021) [15] Two end-to-end deep neural network models for ECG-based authentication are presented. The first model creates a CNN. The second model uses ResNet-Attention, a residual convolutional neural network (ResNet), for human authentication. Two 2-s ECG signals from PTB and CYBHi were used for authentication. ResNet-Attention advised. The Table 2 summarizes the result, Dataset, and methods of related work.

Table 2. Summarized of previse studies

Rf	Year	Dataset	Methods	Result
[12]	2018	PTB (52 subjects from 290 Subjects)	• EMD • KNN • PCA	mAP 95.14%
[13]	2019	• PTB (234 Subject from 290) • CEBSDB • NSRDB • MITDB	• NNC • SVM	Accuracy • PTB 99.54(SVM) 98.71(NNC) • CEBSDB 99.85(NNC) 100(SVM) • NSRDB 92.94(NNC) 95.28(SVM) • MITDB No results reported
[14]	2021	• PTB (100 bject) • ECG-ID	CNN models: GoogLeNet, ResNet, MobileNet, and EfficientNet.	Accuracy • PTB GoogLeNet 99.76 ResNet 100 EfficientNet 99.70 MobileNet 100 Small CNN 99.83 • ECG-ID GoogLeNet 90 Multi 93.87 ResNet 97.28 EfficientNet 83.10 MobileNet 87.51 Small CNN 94.18
[15]	2021	• PTB • CYBHi	CNN ResNet	• PTB Accuracy 98.59 Precision 99.32 Recall 98.33 F1score 98.82 • CYBHi Accuracy 99.72 Precision 100 Recall 99.50 F1score 99.79

5. PROPOSED SYSTEM

Creating data for the biometric security sector was based on ECG. Due to the nature of the type of data available to researchers, it is specialized in the medical topic and the diagnosis of diseases. The main idea was to create relevant data for work by reading, processing, extracting, and then classifying it. The following Figure 1 shows the structure of the proposed system.

5.1. Split Dataset

The data set was approved in two ways. Where the first step is to use the data set with 290 records, and after pre-processing, the data set contains each record, and each person entering 25 backup ECGs of the person and on this new data complete the classification process, where the total data total became It is (13,750) ECG. Then, the data was partitioned into a training set and a test set using the Keras library as the first dividing and second step of splitting data using k-fold for svm and hold-out (3 Cases as CNN), and the procedure for partitioning is laid out in Table 3. Table 4 shows the details of the Dataset.

Table 3. Details of dataset

BTP original	PTB after processors	Training	Test
• 290 Main record • 549 sub-Main record	• 290 records • 13,750 sub-Main record	80% (11,000)	20% (2,750)

Table 4. Categories of PTB

Diagnostic class	Number of subjects
Myocardial infarction	148
Cardiomyopathy / Heart failure	18
Bundle branch block	15
Dysrhythmia	14
Myocardial hypertrophy	7
Valvular heart disease	6
Myocarditis	4
Miscellaneous	4
Healthy controls	52

This data set was utilized for security in the proposed system. It depends only on the person with the ECG, and each individual's information is denoted by (the record name). Due to the nature of the data used to diagnose heart diseases and the lack of security data, the idea of creating data from the original data and preparing it to make a biometric system with additional prints for each person was worked out, and the signaling mechanism was worked out from the same reference numbers for review only. Thus, the initial phase of data preparation for the proposed system involved taking the first step: reading, processing, extracting features, classifying, and identifying the person. Four open records "124, 132, 134, 161" have no personal information. Data webpage.

5.2. Primary Processing Operations

Data processing is a crucial procedure. It is a double-edged sword in that it can either improve the Accuracy of the proposed system or decrease it, depending on how it is implemented. The pre-processing process was necessary and increased the system's efficiency based on the scientific experience and relying on what was published by the researchers in the source [7]. The processing process; went through four initial improved phases as follows:

- ➢ Plot Signal
- ➢ RE-sample
- ➢ Low pass filtering
- ➢ Normalization

The benefit of the first step of the processing process is to convert the values of the records into an image to view, as shown in (a), and then comes the second pre-processing, which is Stage (RE-sample). The purpose of this process is to completely standardize the frequency of each record in the data set from frequency 1000 to frequency 200. The advantage of taking this step is that it makes the signal visible to the human eye in a way comparable to zooming in on the signal to identify the characteristics of each image or badge. Table 5 Shows the describe of the benefit of each step.

Table 5. Describe the benefit of each step

No.	Step	Advantage
1	Plot Signal	Convert CSV. File values to an ECG signal to view humans in the application GUE
2	RE-sample	Frequency uniformity to indicate 200
3	Low pass filtering	Removal of low-frequency noise in the signal
4	Normalization	Standardization of the signal

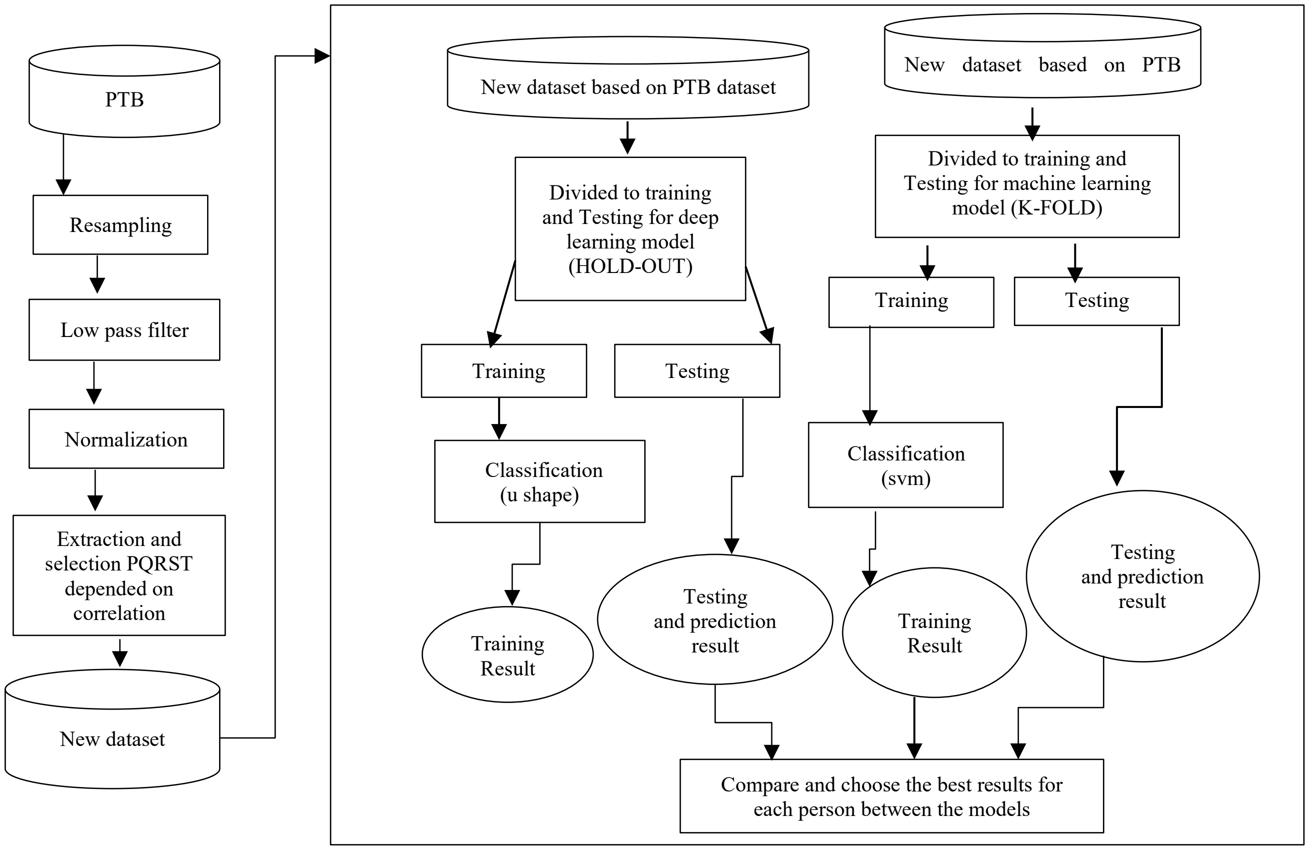

Figure 1. System's block diagram

5.3. Feature Extraction and Selection

It is a plan for machine learning. Still, there is no harm in using it in deep learning, where the basic idea of the proposed system is a single processing process for the algorithm of deep learning and machine learning., where the basic idea of the feature extraction and selection process is to form the reserve fingerprint of the person. One is to configure new data with a character similar to the character of data intended for biometric systems with reliability due to the work of 25 ECG per person based on the six most vital features that have been extracted, these features were extracted, and the best six features were selected based on experience and their impact on the Accuracy of the work, as the features had an impact on Accuracy and time. With high Accuracy, and because the factor of time and Accuracy is essential for any system, the goal is to balance the two, Accuracy and time, because it is a biometric system; the results of selecting more than six features will be included. The new data results will be included in the appendix by extracting the features of the proposed system. Clarify the details of new data exposed in Table 6.

Table 6. Information of Csv Feature File

Total record	Feature	companion	Best feature
13750 (record)	480 Colom of features for each person	25 companions for each person	➢ 6 best features ➢ based on 480 Colom and divide by 80 window sizes equal to the number of features (6)

5.4. Training Model

Training the CNN algorithm is one of the most important basic steps to obtaining Accuracy and high results.

5.4.1. Train Loss

Training loss measures how well a deep learning model fits training data. It measures the model's training-set error. The training set was utilized for training the model. The training loss is computed by adding each example's mistakes. Each batch's training loss is also measured. The training loss curve shows this.

5.4.2. Validation Loss

It measures a deep learning model's validation set performance. The validation set tests the model's Accuracy. The validation loss is determined from the total of each example's errors in the validation set. Table 7 which summarizes the main classes that were adopted in the proposed system to build the neural network. There is a repetition of layers, and the reason for this is that the first input to the algorithm is filtered through the first layer. Because it is a biometric system, the result is stored in a variable. Then a layer similar to the previous layer filters the newly filtered data from the previous layer again. The primary objective of the suggested system is to achieve high Accuracy in the results and classification accuracy. The construction order of these layers was based on the experiment with which several attempts were made to obtain high Accuracy.

Table 7. Summary of a layer in CNN

Layer name	Description
Input layer	It is the feed that goes into the entire CNN. The pixel matrix of the data is frequently represented by it in the neural network used for data processing
Conv	In a deep CNN, the convolutional layer extracts image features. It is also the layer at which filters are applied to the original image or other feature maps
ReLU	activation function that is non-linear and is utilized in multi-layer neural networks (MLN). Because ReLU is an activation function in neural networks, it does not follow a linear pattern. Instead of utilizing the traditional Sigmoid function, which assigns probabilities for each neuron (>50% if X>0), this method assigns the value itself; if X is negative, it assigns 0 as the probability. The function cannot be described as linear because it always equals zero if X is negative yet returns the value of X itself if X is positive. As a result, it cannot be described as linear
Max_Pooling	choosing the greatest number of relevant components from within the scope of the filter's application on the feature map. In this scenario, the consequence of applying the max-pooling layer would be a feature map that includes the most noticeable features from the feature map that came before it
Flatten	The data are first transformed into a one-dimensional array before being input into the subsequent layer. Flattening the output of the convolutional layers will allow you to create a single extensive feature vector. It is also connected to the "fully-connected layer" as the final classification model.
Dense	also known as a fully connected layer, is a layer in a neural network that connects every neuron in the previous layer to every neuron in the next layer. This means that each neuron in the dense layer receives input from all of the neurons in the previous layer, and each neuron in the dense layer outputs a value that is a function of the inputs it receives
SoftMax	Optimizing the neural network's performance requires ensuring the model is reliable by applying the Loss and Cross-Entropy functions. Utilizing the Cross-Entropy function can result in several beneficial outcomes.

• It is important to note that the entered values were placed in the input layer (?), as depicted in Figure 2.

Input-3:inputLayer	Input:[(?,489,1)]
	Output: [(?,489,1)]

Figure 2. The input layer of the system that is being proposed

Which corresponds to (null). The benefit of this step is to make the array accept variable and non-constant values, unlike the second and third values are fixed values, where the array in its final form is (variable values, fixed values, fixed values).

• Stride value starts with (one) and is (fixed)(two) based on an experiment where Stride is the number of pixels that shifts over the input matrix. And can be calculated by using Equation (1).

$$[\{(n+2p-f+1)/s\}+1]\times[\{(n+2p-f+1)/s\}+1] \quad (1)$$

where, padding: p was equal to zero in the proposed system, filter size: $f\times f$ was equal to 3×3 in the proposed system chosen by the experiment, input size: $n\times n$ were equal to 480×1, stride: 'S' output image dimension where the start value is one and stable on two. The anther model training on ML by using SVM, which SVM model represents multiple classes on a hyperplane in a multi-dimensional space. To reduce errors, "the hyperplane" is created repeatedly using "SVM".

This algorithm in the proposed system aims to classify datasets such that the largest marginal hyperplane may be found for each class (MMH). The proposed system uses a Linear Kernel-based system to compute a dot product between two observations. There are two possible solutions to this equation that description in chapter two. According to the equation presented earlier, the sum of the product of each pair of input values constitutes one component of the product of two vectors denoted by "x and x_i". This technique is used in the suggested method to obtain an ECG classification. Analogous to the aforementioned method is the kernel technique, which employs feature maps in an implicit manner through the utilization of the Nystroem method for kernel approximation. The Nystroem technique employs a universal approach to obtain low-dimensional characteristics from kernels. Kernel-approximations. The attainment of this objective may be realized through the selection of a subsample from the data utilized in the assessment of a kernel. The successful execution of Nystroem is contingent upon the utilization of libsvm. The required amount of time increases at least quadratically with the number of samples, and after tens of thousands of samples, it may no longer be viable. Consider utilizing Linear SVM if you have many data to analyze. The main idea of using this algorithm with the deep learning algorithm (CNN) is to hybridize the results partly by comparing the results of each prediction.

5.5 Result of a Proposed System Based on Confusion Matrix

The proposed system depends on Two algorithms, one for deep learning and the second for machine learning, where the two techniques of Hold Out and k-fold Technique were adopted to divide the data set and for evaluation using a confusion matrix [16, 17]. The Experiments training and testing number of DL (CNN) as following:

➢ Deep Learning CNN
• 70% Training and 30% testing
• 80% Training and 20% testing
• 90% Training and 10% testing

To describe the value of the confusion matrix, Table 8. shows the result of models 70-30.

Table 8. The result of model 70-30

Experiments	Training And Testing	Confusion Matrix Values	Result
1	70% Training and 30% testing	TP= 2697 FP= 18 FN= 24 TN= 0	Accuracy: 93.2% Precision: 97.5% Recall: 95.4% F1-score: 96.5%

To describe the value of the confusion matrix, Table 9. shows the result of models 80-20.

Table 9. The result of model 80-20

Experiments	Training and Testing	Confusion Matrix Values	Result
2	80% Training and 20% Testing	TP= 2737 FP= 2 FN= 1 TN= 0	Accuracy: 99.4% Precision: 99.9% Recall: 99.5% F1-score: 99.7%

To describe the value of the confusion matrix, the Table 10 shows the result of models 90-10.

Table 10. The result of models 90-10

Experiments	Training And Testing	Confusion Matrix Values	Result
3	90% Training and 10% Testing	*TP*= 2735 *FP*= 0 *FN*= 5 *TN*= 0	Accuracy: 97.2% Precision: 98.7% Recall: 98.5% F1-score: 98.6%

Note that the change is slight between the three models, but the best result was presented in a percentage of 80% Training and 20% testing based on Experience in CNN.

- **Machine Learning SVM**

Machine learning algorithms depend on another technique different from the deep learning technique (k-fold). This method is the main idea of the random division of five and ten possibilities. In the proposed system, the deep learning algorithm was CNN. The experience proved that the best model was when the data set was divided into 80-20 training and testing where the highest in terms of Accuracy, and the machine learning part two experiments were conducted where the highest in terms of results was 90-10 with a slight difference of tenths from the experience of 80-20, and therefore the experiment was adopted, 20-80 is the best, despite the difference of tenths, which is very simple because the basic idea is that the system in this model was tested on more data, which is what is required. All trial results are included in the appendix. Table 11 shows the confusion matrix values of the SVM algorithm for all mods.

Table 11. Result of three models of SVM

Experiments	Training And Testing	Confusion Matrix Values	Result
1 Ideal model	80% Training and 20% Testing	*TP*= 2688 *FP*= 6 *FN*= 42 *TN*= 0	Accuracy: 98.1% Precision: 99.7% Recall: 98.3% F1-score: 99%
The fold of the ideal model	FOLD0 FOLD1 FOLD2 FOLD3 FOLD4		0.9646522234891676 0.9692132269099202 0.9543899657924744 0.9634911580148318 0.96406160867085
2	90% Training and 10% Testing	*TP*= 2692 *FP*= 6 *FN*= 42 *TN*= 0	Accuracy: 98.2% Precision: 99.7% Recall: 98.4% F1-score: 99.1%

Table 12 describes the results of the confusion matrix, the best model.

Table 12. The Confusion Matrix's Results for The Ideal Model

Algorithm Name	Confusion Matrix Values	Result
CNN	*TP*= 2737 *FP*= 2 *FN*= 1 *TN*= 0	Accuracy: 99.4% Precision: 99.9% Recall: 99.5% F1-score: 99.7%
SVM	*TP*= 2688 *FP*= 6 *FN*= 42 *TN*= 0	Accuracy: 98.1% Precision: 99.7% Recall: 98.3% F1-score: 99%

6. CONCLUSION

Integrating deep learning and machine learning in the results section was a new idea and a new concept in the topic of ECG to identify people's identities. The main idea was to get the best results and compare the results of the two techniques for each person. Moreover, the primary processing process that extracted the features was of high quality because it provided the ability to deal with the electrical signal and create new data dedicated to identifying people by following the principle of alternative fingerprints, where the proposed system provided 25 alternative ECGs per person. After all, heart diseases can distort the electrical signal of the heart. In order to mitigate this issue, efforts were undertaken on this foundation. In addition, a novel approach was employed in which features were extracted, diverging from conventional techniques. These features were subsequently incorporated into deep learning and machine learning models, and the system was able to achieve recognition by leveraging the most optimal features. Additionally, the utilization of pre-existing Python libraries dedicated to cardiac electrophysiology facilitated the feature extraction process, resulting in a contemporary approach to feature extraction without reliance on conventional methods. The system achieves high accuracy through the utilization of two algorithms, namely Convolutional Neural Network (CNN) for deep learning and Support Vector Machine (SVM) for machine learning, in its classification structure.

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