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Improved Healthcare Monitoring of Cardiovascular Patients in Time-Series Fashion Using Deep Learning Model

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Abstract: In this paper, we develop an Improved Healthcare monitoring of cardiovascular patients in time-series fashion using deep learning model. The model uses deep learning via radial basis function integrated with artificial neural network to classify the time-series data from the electrodes. When choosing the algorithm that will be used to determine the forecast, the level of accuracy that is provided by an algorithm is one of the factors that is taken into consideration. The classification is carried out in a time -series fashion and the results of which are monitored in timely fashion. The python simulation is used to design the deep learning model, where the proposed model is used to validate the time series data. The performance of the proposed model is evaluated in terms of how it compares to the performance of models that are already in use through the process of benchmarking. This approach is used in order to determine whether or not the strategy that has been presented is the one that will prove to be the successful in the long run.

Keywords: *Decision Support, Cardio Vascular System, Time Series Forecasting, Deep Learning*

1. Introduction

Heart disease is the top cause of death in the United States, as reported by both the Centers for Disease Control and Prevention (CDC) and the American Health Monitoring Organization [1]. According to the Centers for Disease Control and Prevention (CDC), heart disease affects approximately 74% of the population on a yearly basis. In the case of cardiovascular issues, acquiring a diagnosis and beginning treatment as quickly as possible are both absolutely necessary steps in the fight against complications. The discoveries that have been made in modern medicine have shown that there are important treatments that are also effective for heart problems [2].

As a result of recent developments, intricate strategies including information technology (IT) can now be applied in the treatment of a wide variety of medical disorders. A screening electrocardiogram (ECG), angiography, and blood testing are considered to be the gold standard when it comes to identifying heart illness. The electrocardiogram, which is more commonly referred to as an ECG, is a diagnostic tool that is used in the process of determining whether or not there are problems with the heart [3]. Electrocardiograms, which are more commonly referred to by their abbreviated form, ECGs, are graphical representations of the electrical activity that takes place in the heart [4].

Researchers [5–6] have examined a wide variety of approaches to using machine learning and deep learning in order to autonomously diagnose cardiovascular illness. The utilization of electrocardiogram (ECG) data, often in the form of one- or two-dimensional voltage-amplitude time-series signals, is required for the majority of these techniques. The classification of time series of electrocardiogram (ECG) data makes use of a number of different methodologies, with encouraging results [7].

The feature extraction and classification the hearts beats were recorded from an electrocardiogram [8]. Various ML [9]-[11] is used to diagnose cardiovascular disease after first extracting features from ECG data based on the temporal frequency of the signals using the eigenvalue decomposition of the Hankel matrix and the Hilbert transform. This was done in order to improve the accuracy of the diagnostic process. After they had retrieved characteristics from ECG data via the random forest, they proceeded to execute this next step.

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There is technology available in time that is capable of automatically diagnosing cardiac issues. Despite the fact that these algorithms are capable of making accurate predictions using only a single dimension of ECG beat signals, they have not yet seen widespread use in medical institutions despite having this capability [12].

These are the primary factors that determine the efficacy of these approaches. In addition, the most recent research has shown that traditional methods can achieve good accuracy by using single-lead electrocardiogram images rather than the more common 12-lead ECG images. This is in contrast to the previous research, which used 12-lead ECG images. In contrast to the more frequent technique of using 12-lead ECG images, this approach utilizes only 10 leads [13].

An additional degree of difficulty was added by the fact that the hospitals and clinics all used different ECG equipment and displayed ECG images that were produced in different ways. This was a factor that contributed to the patient condition. The research that has been done up until this point has not been able to produce a unified approach that can be applied to the processing of the various ECG image formats that are now in use [14]. The researchers do not have access to the source images of 12-lead ECGs that are available to members of the general public. The primary objective of this research project is to develop an innovative automatic detection tool that can be used in cardiac hospitals during the process of assessing 12-lead electrocardiogram (ECG) images [15].

It is of the utmost importance to put into place an automated method for the diagnosis of cardiac disorders. This can be accomplished by feeding images of electrocardiograms (ECGs) into a deep neural network that is based on 12 leads. Mathematical models and formulas constitute the basis of a deep neural network. These provide the network with the ability to simulate the cognitive processes of human beings.

Artificial neural networks are driven by mathematical and functional concepts that search for recurring patterns among the numerous nodes that make up the network. A neuron is the basic building block of a deep neural network, and just like a human neuron, it can only acquire new knowledge through direct personal experience. There is a link between the amount of input and the amount of output in the disciplines of training.

The fundamental purpose of this work is to construct a functioning automated model for ECG heart ailment diagnosis that is suitable for implementation on mobile healthcare platforms, according to the introduction to the study.

2. Related Works

Given the relevance of effectively classifying time series data, scholars have developed a variety of approaches for doing so in recent years. Combining a nearest neighbor (NN) classifier has proven to be effective and is widely utilized for TSC. This strategy has been successful despite the passage of time. In particular, it has been demonstrated that the dynamic temporal warping offers an exceptionally stable starting point [16].

After evaluating a variety of different alternatives to DTW produces findings that are appreciably superior to DTW. They also demonstrated that the results obtained by merging multiple NN classifiers while making use of a variety of distance measures were superior to those obtained by any of the individual classifiers [17]. This was demonstrated by the fact that the results obtained by this method were superior to those obtained by any of the individual classifiers. As a result, the primary focus of recent research and development has been on the development of algorithmic frameworks that are substantially more effective than the combination of NN and DTW [18].

These methods either utilize a collection of decision trees (random forest) or a collection of discriminant classifiers on one or more feature spaces. By transforming time series into a different feature space, the majority of these approaches are able to generate outcomes that are noticeably superior than those achieved by the NN-DTW. The shapelet transform and DTW features are two examples of this type of feature. COTE is a collection of 35 different classifiers [19].

COTE combines the results of several different classifiers using the same transformation. HIVE-COTE has been shown to be much more effective than COTE in a number of studies. This was done to meet the aforementioned goal. The HIVE-COTE algorithm is currently the most advanced and effective time series classification method that can be used. After analyzing its performance on 85 datasets from the UCR/UEA collection, we came to this conclusion after evaluating its effectiveness [20].

The extraordinary precision of HIVE COTE comes at the expense of an extremely high computational cost, which makes it hard to apply to a massive data mining scenario that takes place in the real world. This method of training entails training 37 classifiers; hence, depending on the conditions, it may sometimes be difficult or even impossible to apply. It has an unreasonable temporal complexity. The wavelet transformation cannot be applied in any way.

The classification time for the nearest neighbor classifier, which is one of the 37 possible choices, is particularly

lengthy. This is due to the fact that it must initially investigate the training set before arriving at a conclusion during test time. Because HIVE-COTE places such a great focus on the usage of the nearest neighbor, putting it into reality in a real-time context is, at best, challenging. This is because HIVE-COTE places such a significant emphasis on the use of the nearest neighbor. Last but not least, academics already have difficulty grasping the decisions made by a single classifier; as a result, attempting to analyze the findings made by 37 classifiers adds even more time to the already considerable amount of time that is required to run HIVE COTE [21].

This is due to the fact that deep learning has been shown to be effective in various classification tasks. Because deep learning has been shown to be effective in a variety of categorization tasks, this usage of deep learning has been prompted as a result of this success. In recent years, convolutional neural networks, have emerged as a game-changing technique in the realm of computer vision [22].

CNNs were utilized in the field of image identification in order to reach performance on par with that of humans. The application of deep learning was what made this accomplishable. These studies were conducted after the success of DNNs in computer vision. Not only are they having a huge impact on the field of speech recognition, but they are also having a substantial impact on the field of image recognition.

There is a similarity between the tasks of natural language processing and speech recognition, and the majority of this is attributable to the sequential nature of the data, which is also a hallmark of time series data. This similarity is striking because it highlights the similarities between the two types of data. This quality is shared by both natural language processing and speech recognition.

3. Proposed Method

Before feeding the data into the model for the purposes of training, it is necessary to first preprocess the data in its entirety. This is a vital step. At this stage, one can get information by deducing it from the data that is available. The steps that go into the preparation of information are illustrated in Figure 1, which offers a graphical depiction of the process.

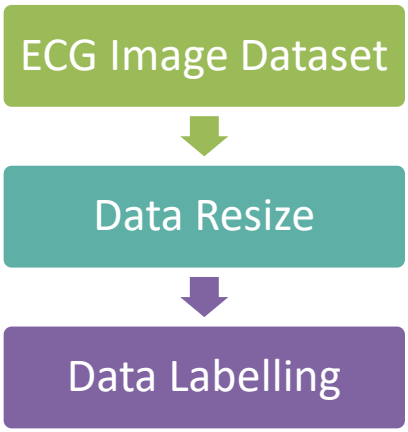

Fig 1: Data preprocessing

Data Resizing

Due to the size of the ECG images, which were on average more than 800 KB per, they required to be modified by hand before the algorithm could be trained. In order to provide a faster and more efficient learning experience, the size of the ECG images was reduced to around 300 KB.

Data Labeling

As a result of our investigation, we were able to collect the labeling details for each of the electrocardiogram 12 leads (ECG). Using the program called LabelImg, the authors of this study labelled the classes that were contained inside the dataset. As a consequence of this, we were given a total of 48 tagged items that were dispersed throughout each of the four categories so that our trained model could identify them.

The ANN is a forward-thinking mathematical model that provides solutions to problems by employing a manner of thinking that is analogous to that of the human brain. The following serves as the theoretical behind for the development of ANNs. The structure of an ANN is comprised of individual components that are referred to as nodes, which are the locations where information processing takes place.

The usage of artificial neural networks in hydrological applications has resulted in the development of a number

of distinct algorithms that are applied during the learning process. These algorithms are used to help the network improve its performance. Based on the body of material that is currently accessible, the method known as radial basis function neural network (RBFNN) is now thought to be superior. Despite the fact that there are a great many other possible approaches to training a neural network, this remains the most common one. The rationale for this is due to the fact that RBFNN provides greater performance in terms of reliability, convergence speed, and extrapolation size.

Figure 2 can see that the RBFNN is composed of three distinct levels. The goal of this inquiry is to develop a forecast for the subsequent flow of the stream, and each layer role is to help achieve that goal. It is the responsibility of the first layer to supply the RBFNN algorithm with the input variables so that it can finish the work it was given. In the second layer, an implementation of a modification of the input variable-neuron connection nonlinear transformation function can be found. The data have been relocated from the space of the hidden layer to the space of the output layer, which is the variable that needs to be changed in order to accomplish the aim.

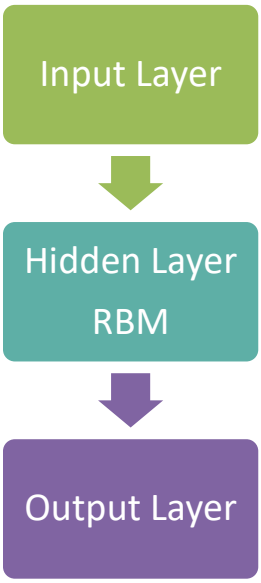

Fig 2: RBF with ANN

Function $\varphi_1, \varphi_2, \ldots \varphi_N$ make up the fundamental hidden transfer functions, and the equation $\{\varphi_i(x)\}$, where N is the hidden domain.

When it comes to pattern recognition applications such as these, the Gaussian function is often the RBF function of choice, and the formula that follows exemplifies the Gaussian representation:

$$\varphi(x,\mu)=e\|x-\mu\|^2d^2 \qquad (1)$$

where

μ - Gaussian function center

x - mean value and

d - center distance of $\varphi(x, \mu)$.

The center and spread d are two distinct characteristics that yet hold the same level of significance in the overall analysis. At the beginning of the modeling process, these two configurations are put up, and successive training iterations enable the subsequent fine-tuning of them.

When using a Gaussian radial function, it is plausible to make the assumption that the hidden unit will be more sensitive to information that is located closer to the center of the distribution. This is because the Gaussian distribution has a center. Adjusting the spread d at the very beginning of the process would allow for a more accurate fine-tuning of the sensitivity of this adjustment.

The concept of feedforward neural networks that only had one hidden layer was presented. These networks only had one hidden layer. Generalized ANNs were developed, and in due time, the need that the hidden layer contain neurons was eventually removed as a necessity for the layer.

Because the hidden layer of the extreme learning machine technology does not need to be adjusted in any way, it has the potential to be an effective alternative to more traditional forms of training. Unlike the gradient descent learning algorithms, it takes into account the lowest norm of output and has highly quick training operations overall. Lastly, it has a decent performance when it comes to generalization.

In this article, we study how the ELM may be used in conjunction with a variety of time interval data series to create predictions about stream flow. Before creating forecasts for the future based on historical knowledge from the past:

$M(t-1), M(t-1)\ M(t-2),$ (2)

$M(t-1)\ M(t-2)\ M(-n),$ (3)

The ELM takes into consideration a variety of various inputs depending on which it gathers information. The network output (predicted M_t) is defined as:

$$f_L(x) = h(x)\beta \quad (4)$$

where

$\beta=[\beta_1,\beta_2,\ldots,\beta_l]^T$ – intermediate weight,

h(x)=$[g_i(x),\ldots,g_l(x)]$ - output of the hidden weight.

L - hidden neurons.

$g_{i(x)}$ - ith hidden output.

The sigmoid activation function, which can be stated as follows, was used in order to aid the evolution of the models that were applied in this research.

$$gi(x)=SigAct(x,ai,bi)=(1+exp(-(aix+bi))) \quad (5)$$

where

a_i - weights of random input and

b_i - intermediate bias.

Utilizing the ELM model is one way to find a solution to the H^{β}=T learning problem. The desired output matrix, which is denoted by the notation $T = [T_1, \ldots, T_N]$, as well as its related covariance matrix, which is marked by

$$H = [h^T(X_1), h^T(X_2), h^T(X_3),\ldots., h^T(X_N)]^T. \quad (6)$$

The output weight β is denoted by the symbol, and its computation is denoted by the equation

$$\beta=H^{\dagger}T, \quad (7)$$

where $H^{\dagger}$ - Moore-Penrose matrix H inverse.

This weight can be found by multiplying the input weight by the output weight. It is essential, when constructing a model for predicting stream flows, to take into consideration how straightforward it will be to put the model into action once it has been developed.

The ELM method key benefit is that it can cut the amount of time needed to finish the training procedure by a sizeable amount. This is made possible by the utilization of a strong mathematical approach that reduces the amount of time spent on ascending and descending steps. This is made feasible by the fact that it can reduce the amount of time that is spent on it by a large amount.

In addition, the amount of time spent computing the weights for the input and output variable, as well as modifying those weights with the least squares solution (linear system), is a substantial amount of time. In conclusion, the method of learning via trial and error is used to the process of taking into account 35 nodes for the hidden layer. This is done to guarantee that the statistical assessment measures are distributed evenly across the model two stages (training and testing).

Univariate time series

A univariate time series (UTS) is a collection of data that is based on a single variable that fluctuates over the course of time. The term univariate time series (UTS) refers to a collection of data that is based on a single variable. Keeping a diary of the relative humidity at each hour of the day is a good example of this concept because it illustrates how it might be used. If we have X and it contains timestamps in the form of t, then we can store it as a list of data points that are organized in chronological order:

$$X = (x1, x2, \ldots, xt) \quad (8)$$

Where xi - data at timestamp $i \in T$ and $T = \{1, 2, ..., t\}$.

4. Results and Discussions

The machine learning repository at UCI, which served as a source, was the location from whence the data on cardiovascular disease originated. The VA Long Beach, Cleveland, Hungary, and Switzerland make up the four different data sources that are now available. This particular data collection includes 303 records in its entirety. Despite the fact that the Cleveland dataset itself contains all 76 of those qualities, the data set that is made available in the repository only includes 14 of those attributes. The Cleveland dataset itself contains all 76 of those properties.

Nevertheless, only one of these components can be considered the output or predicted component at any one time. A set of thirteen criteria can be used to predict whether or not a patient has heart disease; however, only one of these factors can be regarded the output factor. Predicting whether or not a patient has heart disease can be done using these factors. The num property of the Cleveland dataset, which has a range from 0 to 4, serves as a reflection of the severity of cardiac disease in the Cleveland dataset.

The TSFDL performs better than linear regression in terms of both mean square error and root mean square error, we are able to say with complete assurance that our model is the more accurate predictor. This is because mean square error and root mean square error are measures of accuracy.

However, in order to successfully suppress errors, it is possible that this assumption, in addition to a huge number of others, will need to be inaccurate. When you were trying to forecast values with a level of precision that was adequate for the task at hand, it is likely that you made

incorrect assumptions or employed characteristics of a quality that was not up to par. Both of these are potential causes.

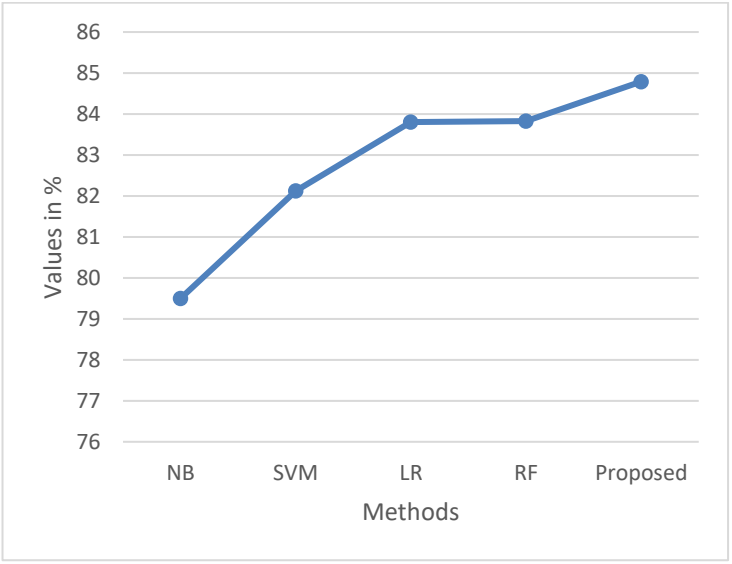

Fig 3: Accuracy

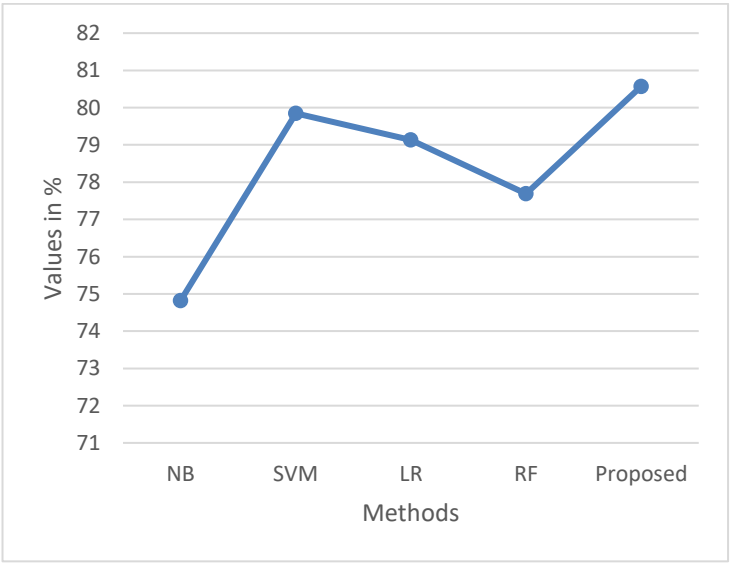

Fig 4: Sensitivity

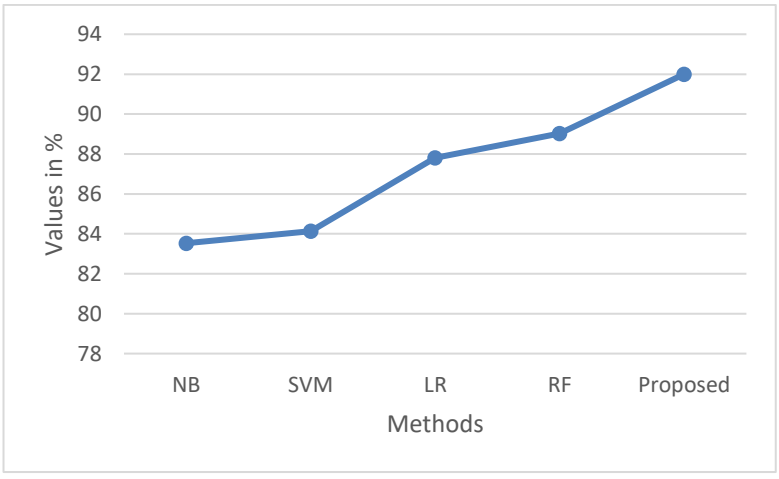

Fig 5: Specificity

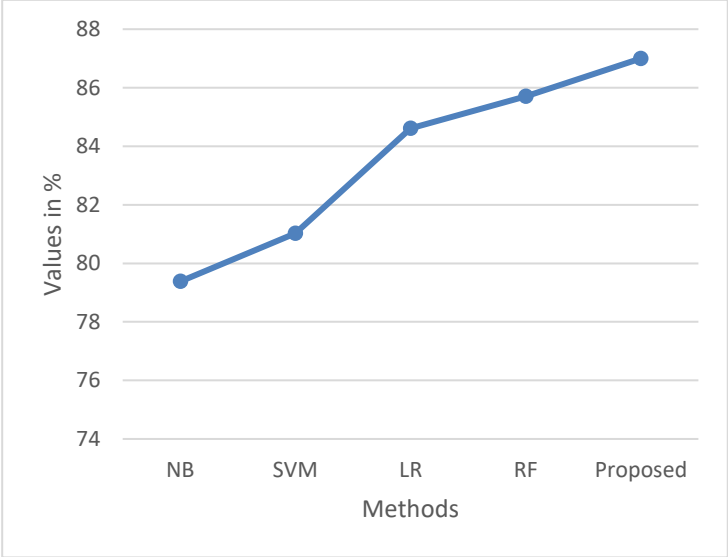

Fig 6: Precision

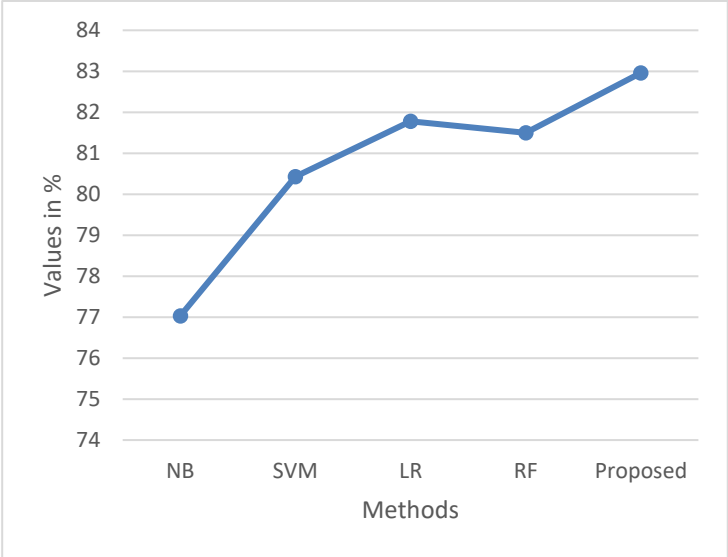

Fig 7: F-Measure

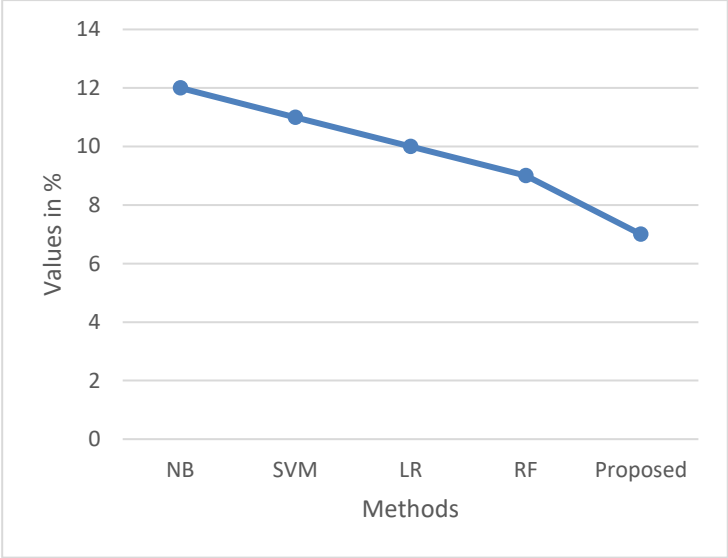

Fig 8: Classification Error

Table 1: Results of Testing

Classifier	Accuracy	Sensitivity	Specificity	Precision	F-measure
NB	83.99	80.85	87.07	86.10	83.40
SVM	84.90	82.09	87.69	86.86	84.41
LR	85.53	83.33	87.69	87.06	85.15
RF	85.84	82.71	88.93	88.09	85.31
Proposed	87.62	85.41	89.81	89.22	87.24

TSFDL is trained with the help of the characteristics of the dataset, and the numbers that are displayed above are the prediction values that were produced as a direct result of the training (Fig. 3-7). The result of testing shown in Table 1. The concept of TSFDL, which may be utilized in forecasting, was introduced right at the start of the conversation. At this stage in the course, one of the many subjects that was addressed was the many kinds of TSFDL.

The study used TSFDL to our data, and it is until that stage in the process that was finally able to get my projected values to match my actual ones. During the course of the entire procedure, this was the very first time that it had taken place. We made the discovery that the values that were estimated were the ones that were the ones that were the ones that were the most comparable to the actual expenses. The benefits get really near to matching the real values, but they do not exactly correspond one to one with the other.

Utilizing the properties that were collected from the datasets allowed for the achievement of this level of precision. An enhancement in the precision of these measures can also be contributed to by the development of more advanced computer systems and data sets. The illustration provides a comparison of the overall performance of all of the algorithms. During the process of designing the interface, the user convenience of use was a primary consideration that was taken into account with reduced classification errors as in Figure 8.

5. Conclusions

In this paper, we utilized techniques from the field of machine learning in order to carry out an analysis on unstructured data and come at novel conclusions on cardiovascular disease. When it comes to attempting to forecast the beginning of cardiovascular illness, the medical world is up against a formidable challenge. On the other hand, the mortality rate is substantially less likely to be a problem if the condition is recognized in its earliest stages and preventative measures are taken. This is because early detection of the disease allows for more time to take preventative measures.

Both the number of features that are chosen and the outcomes that are produced by the model can be used to arrive at an estimate of the level of precision that can be achieved. The TSFDL does not impose any limitations or constraints on the functionalities that can be utilized. The fact that this model can be improved in every conceivable way leads to the achievement of the highest quality outcomes.

References

[1] Li-wei, H. L., Adams, R. P., Mayaud, L., Moody, G. B., Malhotra, A., Mark, R. G., & Nemati, S. (2014). A physiological time series dynamics-based approach to patient monitoring and outcome prediction. *IEEE journal of biomedical and health informatics*, *19*(3), 1068-1076.

[2] Piccialli, F., Giampaolo, F., Prezioso, E., Camacho, D., & Acampora, G. (2021). Artificial intelligence and healthcare: Forecasting of medical bookings through multi-source time-series fusion. *Information Fusion*, *74*, 1-16.

[3] Harutyunyan, H., Khachatrian, H., Kale, D. C., Ver Steeg, G., & Galstyan, A. (2019). Multitask learning and benchmarking with clinical time series data. *Scientific data*, *6*(1), 1-18.

[4] Mongan, W. M., Rasheed, I., Ved, K., Levitt, A., Anday, E., Dandekar, K., ... & Fontecchio, A. (2016, December). Real-time detection of apnea via signal processing of time-series properties of RFID-based smart garments. In *2016 IEEE Signal Processing in Medicine and Biology Symposium (SPMB)* (pp. 1-6). IEEE.

[5] Wu, M., Ghassemi, M., Feng, M., Celi, L. A., Szolovits, P., & Doshi-Velez, F. (2017). Understanding vasopressor intervention and weaning: risk prediction in a public heterogeneous clinical time series database. *Journal of the*

American Medical Informatics Association, *24*(3), 488-495.

[6] Luo, Y., Xin, Y., Joshi, R., Celi, L., & Szolovits, P. (2016, February). Predicting ICU mortality risk by grouping temporal trends from a multivariate panel of physiologic measurements. In *Thirtieth AAAI conference on artificial intelligence*.

[7] Crump, C., Saxena, S., Wilson, B., Farrell, P., Rafiq, A., & Silvers, C. T. (2009). Using Bayesian networks and rule-based trending to predict patient status in the intensive care unit. In *AMIA Annual Symposium Proceedings* (Vol. 2009, p. 124). American Medical Informatics Association.

[8] Vistisen, S. T., Johnson, A. E., & Scheeren, T. W. (2019). Predicting vital sign deterioration with artificial intelligence or machine learning. *Journal of clinical monitoring and computing*, *33*(6), 949-951.

[9] Fortuin, V., Baranchuk, D., Rätsch, G., & Mandt, S. (2020, June). Gp-vae: Deep probabilistic time series imputation. In *International conference on artificial intelligence and statistics* (pp. 1651-1661). PMLR.

[10] Castiñeira, D., Schlosser, K. R., Geva, A., Rahmani, A. R., Fiore, G., Walsh, B. K., ... & Santillana, M. (2020). Adding continuous vital sign information to static clinical data improves the prediction of length of stay after intubation: a data-driven machine learning approach. *Respiratory Care*, *65*(9), 1367-1377.

[11] Gao, N., Xu, Y., Tu, L., Zhu, S., & Zhang, S. (2022). Deep Learning-Based Emergency Care Process Reengineering of Interventional Data for Patients with Emergency Time-Series Events of Myocardial Infarction. *Journal of Healthcare Engineering*, *2022*.

[12] Ramkumar, M., Basker, N., Pradeep, D., Prajapati, R., Yuvaraj, N., Arshath Raja, R., ... & Alene, A. (2022). Healthcare Biclustering-Based Prediction on Gene Expression Dataset. BioMed Research International, 2022.

[13] Maweu, B. M., Shamsuddin, R., Dakshit, S., & Prabhakaran, B. (2021). Generating Healthcare Time Series Data for Improving Diagnostic Accuracy of Deep Neural Networks. *IEEE Transactions on Instrumentation and Measurement*, *70*, 1-15.

[14] Manikandan, R., Sara, S. B. V., Yuvaraj, N., Chaturvedi, A., Priscila, S. S., & Ramkumar, M. (2022, May). Sequential pattern mining on chemical bonding database in the bioinformatics field. In AIP Conference Proceedings (Vol. 2393, No. 1, p. 020050). AIP Publishing LLC.

[15] Tipirneni, S., & Reddy, C. K. (2022). Self-Supervised Transformer for Sparse and Irregularly Sampled Multivariate Clinical Time-Series. *ACM Transactions on Knowledge Discovery from Data (TKDD)*, *16*(6), 1-17.

[16] Surendiran, J., Theetchenya, S., Benson Mansingh, P. M., Sekar, G., Dhipa, M., Yuvaraj, N., ... & Alene, A. (2022). Segmentation of Optic Disc and Cup Using Modified Recurrent Neural Network. BioMed Research International, 2022.

[17] Ben-Israel, D., Jacobs, W. B., Casha, S., Lang, S., Ryu, W. H. A., de Lotbiniere-Bassett, M., & Cadotte, D. W. (2020). The impact of machine learning on patient care: a systematic review. *Artificial Intelligence in Medicine*, *103*, 101785.

[18] Horn, M., Moor, M., Bock, C., Rieck, B., & Borgwardt, K. (2020, November). Set functions for time series. In *International Conference on Machine Learning* (pp. 4353-4363). PMLR.

[19] Deasy, J., Liò, P., & Ercole, A. (2020). Dynamic survival prediction in intensive care units from heterogeneous time series without the need for variable selection or curation. *Scientific Reports*, *10*(1), 1-11.

[20] Mehrdad, S., Shamout, F. E., Wang, Y., & Atashzar, S. F. (2022). Deterioration Prediction using Time-Series of Three Vital Signs and Current Clinical Features Amongst COVID-19 Patients. *arXiv preprint arXiv:2210.05881*.

[21] Melin, P., Monica, J. C., Sanchez, D., & Castillo, O. (2020, June). Multiple ensemble neural network models with fuzzy response aggregation for predicting COVID-19 time series: the case of Mexico. In *Healthcare* (Vol. 8, No. 2, p. 181). MDPI.

[22] Aruna R, D., Surendran S, D., Yuvaraj N, D., & Debtera, B. (2022). An Enhancement on Convolutional Artificial Intelligent Based Diagnosis for Skin Disease Using Nanotechnology Sensors. Computational Intelligence and Neuroscience, 2022.

[23] Soundararajan, R., Stanislaus, P.M., Ramasamy, S.G., Dhabliya, D., Deshpande, V., Sehar, S., Bavirisetti, D.P. Multi-Channel Assessment Policies for Energy-Efficient Data Transmission in Wireless Underground Sensor Networks (2023) Energies, 16 (5), art. no. 2285,