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# Hybrid Deep Learning Model for Heart Disease Prediction Using Recurrent Neural Network (RNN)

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**Abstract**

*In this paper, we use a recurrent neural network (RNN) that combines multiple gated recurrent units (GRUs), long short-term memory (LSTM), and the Adam optimizer to develop a new hybrid deep learning model for heart disease prediction. This proposed model yielded an excellent accuracy of 98.6876%. This proposed model is a hybrid of GRUs and RNNs model. The model was developed in Python 3.7 by integrating multiple GRUs and RNNs working with Keras and Tensorflow as backends for the deep learning process and is supported by various Python libraries. A recent existing model using RNN achieved 98.23% accuracy, and Deep Neural Network (DNN) achieved 98.5% accuracy. Common drawbacks of existing models are poor accuracy due to the complex design of neural networks, large numbers of neurons with redundancy in neural network models, and Cleveland imbalanced datasets. Experiments were performed using different fitting models, and the results showed that the proposed model using RNN and several GRUs with synthetic minority oversampling technique (SMOTe) achieved the highest level of performance. it was done. This is the most accurate result of his RNN using the Cleveland dataset and shows promise for early prediction of heart disease in patients.*

## 1. Introduction

Heart disease is the leading cause of death in the United States and worldwide [1]. The most common type is coronary artery disease, which can cause heart attacks [2]. Health factors such as cholesterol, blood pressure and glucose control contribute to cardiovascular health [3]. Major factors leading to heart disease include family genetics, high blood pressure, cholesterol, gender, age, diet, calcium levels, vasodilation, and lifestyle. Heart disease has become one of the leading causes of death worldwide [2].

This paper aims to improve the accuracy of heart disease prediction and achieve better accuracy compared to existing RNN deep learning models [5]. A Deep Learning approach for modeling sequential data is Recurrent Neural Networks (RNN). RNNs were the standard suggestion for working with sequential data before the advent of attention models. Specific parameters for each element of the sequence may be required by a deep feed forward model. It may also be unable to generalize to variable-length sequences. Neural networks imitate the function of the

human brain in the fields of AI, machine learning, and deep learning, allowing computer programs to recognize patterns and solve common issues.
Artificial intelligence (AI), machine learning, and deep learning are technologies that have permeated healthcare systems and industry over the past decades [6]-[12].
Deep learning gives the healthcare industry the ability to analyze data at breakneck speed without sacrificing accuracy. Deep learning works similarly to the human brain, using statistical data in mathematical models [11]. Deep learning consists of multiple neurons and layers that rely on neural networks that can micro-analyze data to produce expected and desirable results [13]. Deep learning is very important for accurate and meticulous prediction of heart disease to reduce early detection of patients.

An efficient medical disease prediction model called Gray Wolf Optimization (GWO) + RNN. It uses the GWO algorithm for feature selection and removes irrelevant and redundant attributes. The Auto-Encoder (AE)-based RNN method improved the performance of prediction, avoiding the feature dimensionality issue, and yielding 98.2% [14]. Removing attributes from the data set reduces the quality of predictions. The original version of his GWO algorithm has several drawbacks, including: Poor solution accuracy, poor local search capability, and slow convergence [15], [16]. The Advance RNN model with multiple GRUs produced 98.4%, but the model takes a long time to process. Models tend to crash due to memory exhaustion caused by a large number of neurons in the model [5]. Machine learning algorithms and techniques are highly accurate in predicting heart-related diseases, but the scope of research needs to shape, especially to address the problems of high-dimensional data and over fitting.

One of the problems in predictive performance of the system is poor data quality. The most common data quality problem is missing and irrelevant values. Missing value imputation is useful for filling gaps in training data and improving data quality [17]. A lot of research can also be done on the appropriate ensemble of algorithms to use for a particular type of data [18]. The Cleveland heart disease dataset, obtained from the Universal Child Immunization (UCI) Repository, will be used as the primary source of information for this proposed model.
A deep learning ensemble model using LSTM and GRU maintained an accuracy of 85.71. Future work in this study can be performed using various mixtures of ML and DL models for better predictions [19].

### 1.1. Literature Review

Cardiovascular disease is the leading cause of death worldwide and a major public health problem. Another common problem in health analysis is imbalance in the distribution of data sets, especially in predicting heart disease [1]. In this paper, we use SMOTe's new under sampling scheme to overcome the problem of imbalanced data sets and insufficient real data. Future work demands should be done on larger datasets so that the accuracy of the deep learning models is maintained and preserved. SMOTe synthesizes small class datasets into a larger balanced dataset [21]. The following sections will explore research in artificial intelligence, machine learning, and deep learning in more detail**.**

#### 1.1.1 Artificial intelligence (AI)

Artificial intelligence (AI) is artificial intelligence designed by machines and computers to think and act like humans. It can run learned data patterns, analyze information, and solve problems similar to the human brain [5], [22]. AI is powerful and efficient in healthcare, especially in

critical areas such as early disease detection, treatment management, disease and critical event prediction, and disease assessment. AI provides cognitive capabilities for managing healthcare and facilitating automatic updates of medical information across other healthcare platforms. AI's extraordinary ability to provide more accurate analytical results, minimize errors in clinical data, inform about real-time health risks, and make robust predictions will ultimately improve the quality of care. are the main reasons for using AI in medicine [6].

### 1.1.2. Machine learning (ML)

Machine learning (ML) is a subset of AI that uses statistical and numerical computations to perform analytics [23]. ML requires algorithms to cover the learning process on the data in order to process and produce the final result. The focus was on developing applications that learn from data and improve accuracy over time without programming. An algorithm is a series of statistical processing steps. Algorithms called training are run many times to find patterns and features in huge amounts of data. Finally, the final output is created based on powerful algorithms and available data.

### 1.1.3. Deep learning (DL)

Deep learning is a branch of machine learning in which suitable algorithms are augmented by neurons and layers of brain structure and function called artificial neural networks. Deep learning replicates human brain functions in data processing and analysis to make decisions [10], Deep learning uses hierarchical layers of artificial neural networks to perform a deep analytical process to learn a dataset very rigorously. The learning process in deep learning runs just like the human brain, from input to final output, with several hidden layers in between, and each hidden layer has neurons. A neuron is also known as a node that holds and analyzes specific data previously dictated by a neural network algorithm and transfers the partially processed data to another layer of the neural network. Deep learning process data uses a non-linear approach to connect and associate all inputs to produce the optimal output. The first layer of a neural network collects input data, processes it, and sends it as output to the next layer. The next layer of neurons in a deep learning neural network processes previous information before making decisions and producing final results. Artificial Neural Networks (ANNs) are a class of nonlinear statistical models that have been very successful in the context of deep learning. When assembled with many layers, ANNs can be tuned and often achieve high prediction accuracy [24], [25].

### 1.1.4. RNN

RNN is a class of deep learning-oriented algorithms that follow a sequential approach. The uniqueness of RNNs comes from the connections between hidden layers. Replicate the same hidden layer many times, applying the same weights and biases to the input at each time step. The network runs processes in a loop, changing and updating hidden states and saving data to internal memory. RNN builds a model by training from each data.

The model is updated and rebuilt each time data passes through the RNN chain. RNNs are very easy to understand the data during the training process, can handle both numerical and categorical data, require little data preparation to validate the model with statistical tests, and can be used on large data sets works well with sets [5], [26]. RNNs use cluster points of data within feature groups in their statistical algorithms. Due to the different types of variables, large data becomes complex, making the process of classification and clustering difficult [26]. RNNs

also have a storage facility that they use to capture updates and record them in their neuron units. This is an advantage when working with time series data and gives RNNs a unique quality in deep learning models. RNNs can collect data from arbitrarily long sequences. While making predictions, RNNs capture the sequential information present in the input data and the dependencies between words in the text. Figure 1 shows the RNN and feed forward process of a neural network for a data sequence. RNNs have powerful advantages in data processing and backpropagation capabilities, which consist of detailed analysis of each hidden layer of the neural network.

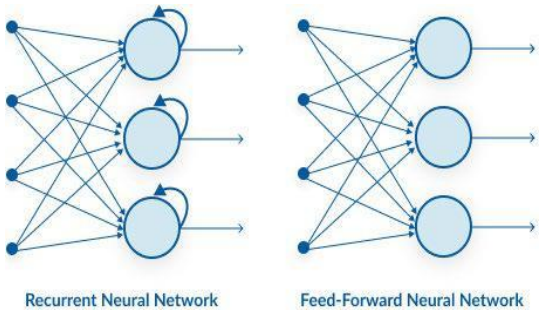


Figure 1. Difference between RNN and feed forward neural network [21]

### **1.1.5** Keras

Keras is an open source machine learning library written in Python and is commonly used to rapidly build deep learning models. It is a high-level application programming interface (API) that runs on Tensor flow, Theano, and CNTK to complete large and complex numerical computations. Keras provides a convenient solution to deep learning problems and saves the effort of building complex networks [29]. Keras overcomes complex neural network processes into a highly simplified solution supported by tf [29]. The Keras module is the official front end for Tensor flow, the most popular API among other deep learning libraries [30].

### **1.1.6 Tensor flow**

Tensor flow is an end-to-end open source machine learning platform [5]. Tensor flow is an open-source math and large-scale machine learning library that combines machine learning algorithms and deep learning models for greater efficiency. Tensor flow runs processes on neural networks to learn patterns of data behavior based on available data and integrates them into the Tensor flow database. Tensor flow's database is huge, with libraries for neural networks, statistical and numerical computations. Tensor flow works at scale in a variety of environments. Tensor flow uses data flow diagrams to represent computations, shared state, and operations that modify that state [31].

### **1.1.7 Critical Analysis**

Table 1 shows an analysis of existing RNN deep learning models for predicting heart disease. F Ali et al. [32] gave the highest accuracy of 98.5%. Most deep learning models exhibit learning redundancy, where the neural network of the deep learning model must train on specific data and remember patterns of behavior for a specific data set. Redundancy is a major cause of data

prediction inefficiency. Bab et al. [14] returns 98.23% using her GWO optimization with RNN. The original version of the Gray Wolf Optimization Algorithm (GWO) has several drawbacks: B. Poor solution accuracy, poor local search ability, and slow convergence [15], [16]. Krishna etc. [5] developed an extemporaneous HIS RNN using 98.4% multiple GRUs. In this paper, we improve this model to increase accuracy using the optimal number of his GRUs and the optimal learning rate.

Table 1. Critical analysis of existing RNN deep learning models on heart disease prediction

| Author | Year | Technique | Drawbacks |
|---|---|---|---|
| [32] | 2020 | Selection of features and ensemble deep learning model. Accuracy = 98.5% | Some features are neglected. |
| [14] | 2018 | RNN with grey wolf optimization (GWO) and auto encoder based. Accuracy = 98.23 | GWO neglect some of the attributes. |
| [33] | 2019 | $\chi$ 2 statistical model configured deep neural network (DNN) accuracy of 93.33% | Redundancy of data and inefficiency in data analysing. |
| [34] | 2020 | Stacked+LSTM+BRNN (Model Accuracy = 93.22% | The first four LSTM layers are activated using sigmoid activation function. |
| [35] | 2018 | RNN with Theano Accuracy = 92% | Training of RNN models are exploding and gradient vanishing. Theano uses long compile times for large models. |
| [36] | 2020 | A stacked-GRU based Recurrent Neural Network model Accuracy of 84.37% | Learning rate low with GRU and RNN. |
| [26] | 2019 | Prognosis prediction using RNN (PP- RNN). Accuracy of 98% | Redundancy of data during deep analysing in hidden layers. |
| [1] | 2020 | Bi-directional Long Short Term Memory with Conditional Random Field (BiLSTM-CRF) Accuracy of 90.04% | Redundancy of data and inefficiency in the architecture of the neural network. |
| [19] | 2020 | Hard Voting ensemble-method approach retained. Surpass Machine learning technique, LSTM and GRU. Accuracy of 85.71% | Redundancy of data and inefficiency in the deep analysing of each parameter through out the hidden layers. |
| [5] | 2020 | The presence of multiple gated recurrent unit (GRU) have improvised the RNN model performance with 98.4% of accuracy. | The performance of the model can be improved. |

## 2. Methodology

In this paper, we propose a hybrid deep learning model designed with RNN and GRU supported by Keras and Tensor flow as backends. The dataset has 313 samples, which we found to be a small size dataset and unbalanced. Imbalanced datasets are primarily relevant in the context of supervised machine learning with more than two classes. Unbalanced data classification is one of the problems that emerged as machine learning evolved from science fiction to applied technology [21]. The complexity of imbalanced data classification arises because imbalances in datasets occur very frequently [37]. Therefore, the data set is synthesized by oversampling using the SMOTe method. The main purpose of SMOTe is to balance imbalanced datasets by randomly regenerating the dataset's minority classes. SMOTe synthesizes new instances from minority classes to establish data equivalence [21], [37]. Correlate the best dataset regeneration to correlate the balance data by performing linear interpolation of the minority class of instances and randomly choosing the k nearest neighbors (ANN) of each instance of the minority class [38].

### 2.1 Development of Proposed Model

RNNs are being developed together with GRU to form robust hybrid neural networks. Figure 2 shows the five main steps used to develop the proposed model. Preparation work is very

important to ensure data collection and data quality. The dataset used in this study is from the UCI repository consisting of her 303 patients undergoing angiography. The Cleveland data are processed to minimize noisy data with missing values for her 6-row features in the dataset. The processed data should comply with standards before passing through the proposed neural network. Various studies of deep learning and hybrid models were thoroughly studied before the idea of this proposed model was drafted.

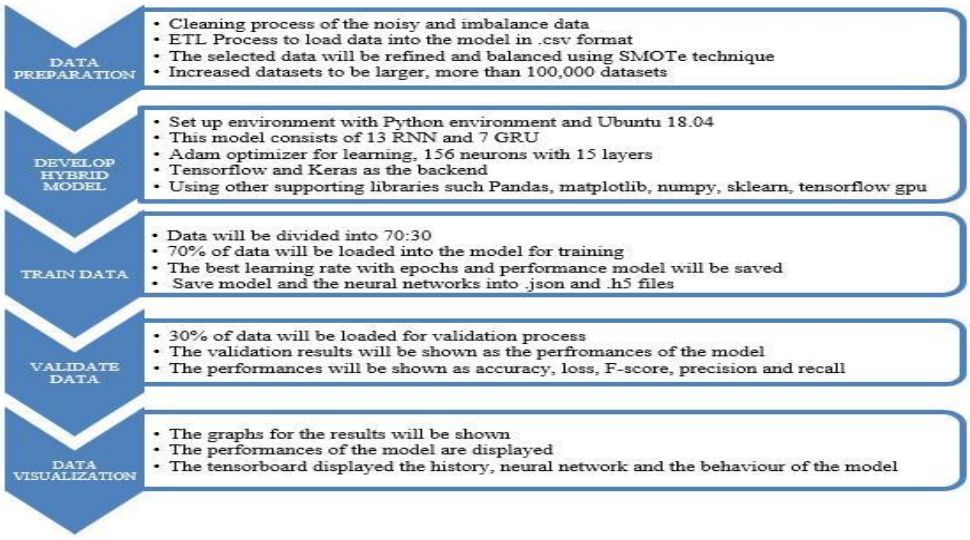


Figure 2: Methodology proposed model

### 1.2 Proposed Model

The proposed model can be divided into three components: data processing, data analysis, and data visualization. The first component of the model uses SMOTe to perform an ETL (Extract Transform Load) process to overcome the imbalanced nature of the Cleveland dataset. This technique generates synthetic data for minority classes by oversampling, making the Cleveland dataset more balanced, higher quality, and larger.

The second component is the critical part where predictive analytics are performed as part of data analysis. Predictive analytics for this component was developed using an RNN and 7 GRUs. As layers with specific activation functions are added to the neural network, the gradient of the loss function approaches zero, making the network difficult to train. Stacked normalization layers therefore improve the learning rate and training of models through Adam optimization. The trained model with optimal epoch, data batch size and redundancy is saved in json or h5 format. The learning rate is varied to select the accuracy of the trained model.

The third component visualizes the behavior patterns of the proposed model in Tensor board graphs. At the end of this process, a final forecast results file is generated and saved. It shows the entire process of the model, showing the overall performance of the proposed model, detailed analysis and sub-processes.

The proposed model produces higher accuracy compared to other RNN-based deep learning models. In line with our ultimate goal of further improving prediction accuracy, this hybrid deep learning prediction model merges the best prediction datasets from previous model trainings. RNN gathers all the information over time during model training for time series

forecasting using backpropagation. Stacking multiple GRUs increases model complexity. Different GRUs record different layers of the RNN to improve accuracy during training, solely due to its ability to remember previous inputs. Adam optimization can tune and choose the optimal learning rate to improve model accuracy and generate optimal weights for the proposed model. This proposed hybrid prediction model outperforms RNN due to the presence of multiple GRUs in the model's hidden layer, as shown in Figure 3.

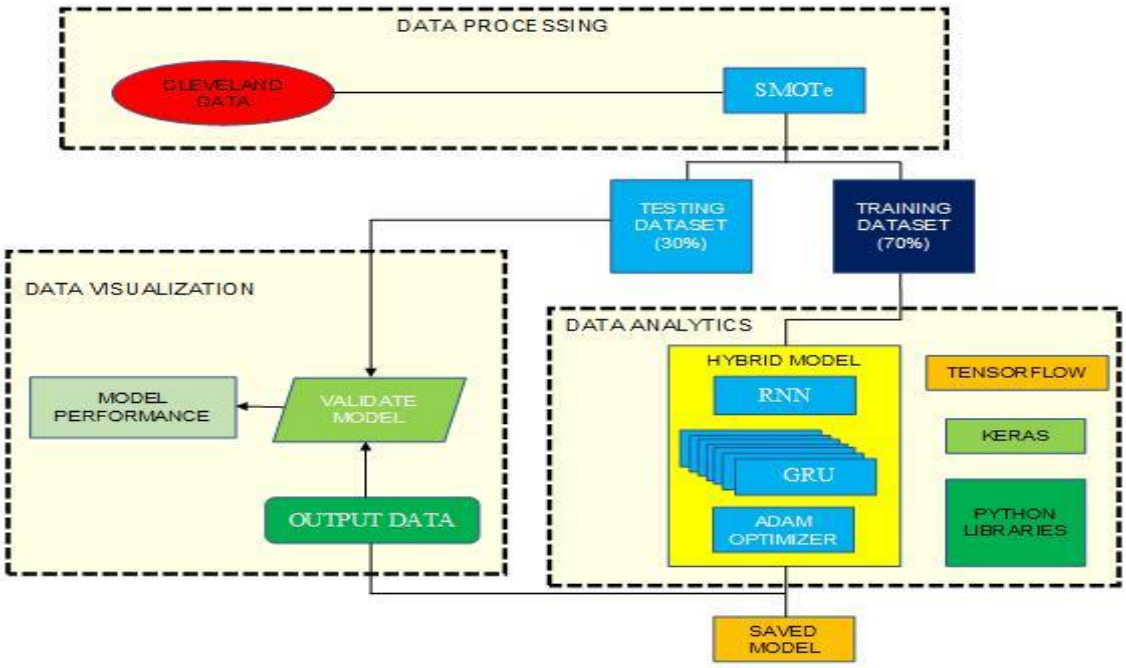


Figure 3: The structure of proposed model

**3. Results and Discussion**

Once the proposed model has been trained and tested, results are generated. The data used for training is segregated from testing, which amounts to 70:30. The proposed model allows optimal training with small data batch sizes. This small batch size of the Cleveland dataset is perfect for RNN and GRU to make better predictions in our tests. Figure 4 shows an accuracy of 97.9869 before the proposed model moves near her 3,000,000 epochs. Results were generated over several training sessions. Trained models and networks are saved in .json and .h5 files. The next time a new dataset is tested, the previously trained model is used to generate final results.

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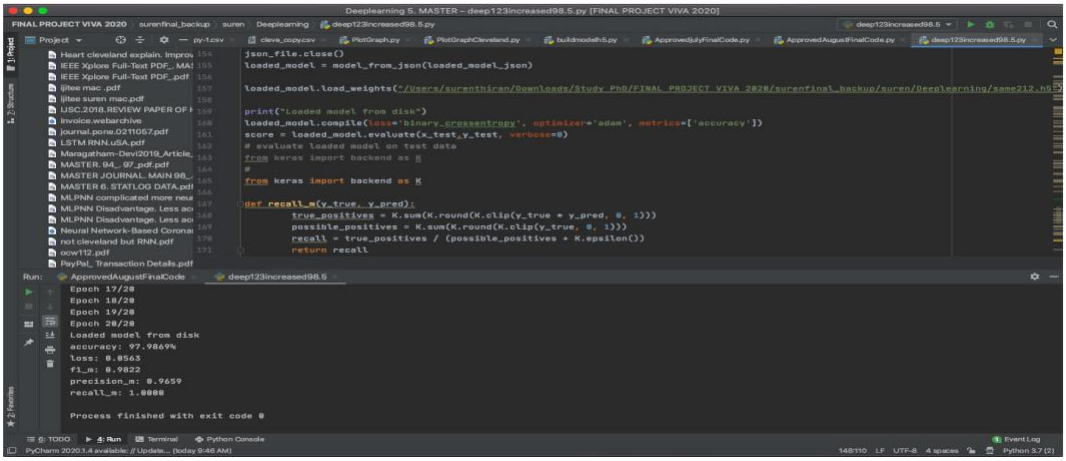


Figure 4: Results of RNN with GRU

Figure 5 shows the final result of the proposed model, which is 98.6876%. This level of accuracy is the best of existing deep learning models for RNNs. This model was trained several times and the model performance such as accuracy, loss, f1 score, accuracy, and recall score are recorded in Table 2. The maximum epoch is about 4,330,350, which took about 192 hours on a stable machine with a GPU as a model booster. Previously, the proposed model was known to crash after every large amount of training. In Ubuntu and Pycharm environments, the training process stalls due to excessive use of computer RAM.

As shown in Table 3, the proposed model is shown to outperform other existing RNN models. Complex RNNs with a large number of hidden layers and neurons are simplified and run faster on the GRU. The importance of RNN and GRU was debated and reached 98.4% [5], while the proposed model reached 98.6876%. This improvement was achieved by implementing the correct number of GRUs in the RNN. The proposed model turned out to be faster due to the Ubuntu environment and the presence of the GPU.

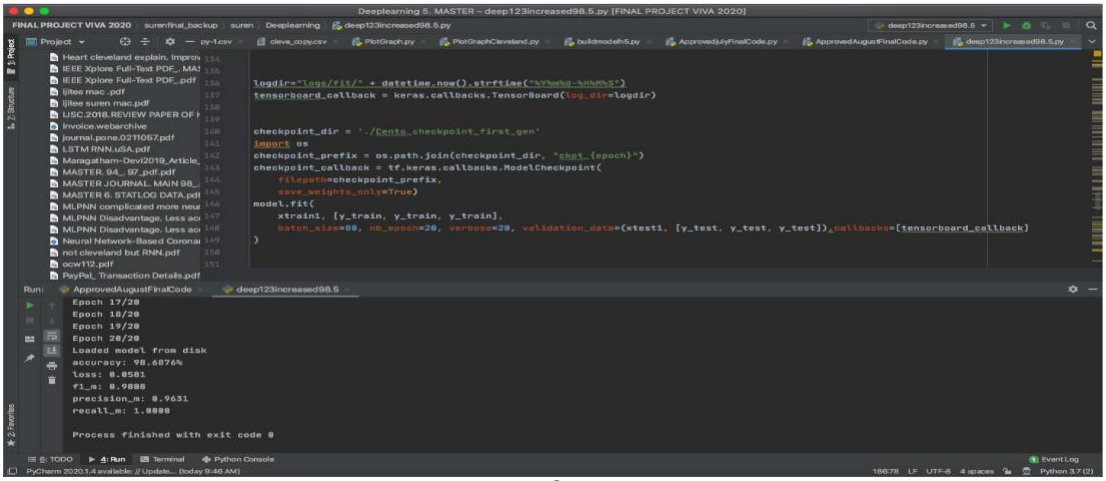

Figure 5: Final results of proposed model

Table 2. Results of proposed model

| Epochs | Accuracy (%) | Loss | F1_m | Precision_m | Recall_m |
|---|---|---|---|---|---|
| 500,000 | 97.3876 | 0.0865 | 0.8908 | 0.9409 | 0.9190 |
| 1,000,000 | 97.3876 | 0.0824 | 0.8918 | 0.9451 | 0.9210 |
| 1,500,000 | 98.3876 | 0.0875 | 0.9018 | 0.9465 | 0.9218 |
| 2,000,000 | 97.3876 | 0.0732 | 0.95238 | 0.9483 | 0.9219 |
| 2,500,000 | 97.3876 | 0.0876 | 0.9348 | 0.9452 | 0.9338 |
| 3,000,000 | 98.1876 | 0.0732 | 0.9368 | 0.9496 | 0.9459 |
| 3,500,000 | 98.3876 | 0.0762 | 0.9478 | 0.9435 | 0.9689 |
| 4,000,000 | 98.2876 | 0.0692 | 0.9508 | 0.9531 | 0.9872 |
| 4,330,350 | 98.6876 | 0.0581 | 0.9808 | 0.9631 | 1.0000 |
| 4,500,000 | 97.6876 | 0.0531 | 0.9748 | 0.9602 | 0.9882 |
| 5,000,000 | 97.1876 | 0.0569 | 0.9738 | 0.9611 | 0.9879 |

Table 3: Comparison of proposed model with existing model

| Model | Accuracy (%) | Specificity (%) | Sensitivity (%) |
|---|---|---|---|
| RNN [14] | 98.23 | 97.6 | 99.1 |
| Back propagation neural network [39] | 98.2 | 89.65 | 87.64 |
| RNN [35] | 92 | - | - |
| Prognosis prediction using RNN (PP-RNN) [26] | 98 | 98.08 | 98.47 |
| Advanced RNN with GRU [5] | 98.4 | 98.4 | 99.1 |
| Proposed model | 98.69 | 96.31 | 1.0000 |

## 4. Conclusion

In this article, we applied the SMOTe method to solve the data imbalance problem. A hybrid model is designed with RNN and GRU and has been successful in improving prediction accuracy. RNN with GRU selects attributes for classification and predicts disease based on priority during model training. RNNs have the advantage of being able to process data instances independently of previous instances. A GRU can store data behavior faster during training than an RNN, which discards unnecessary data during model training. The proposed model performs well on large data sets of over 100,000 samples compared to existing studies.

**References**

[1] A. Baccouche, B. Garcia-Zapirain, C. C. Olea, and A. Elmaghraby, "Ensemble deep learning models for heart disease classification: A case study from Mexico," *Information*, vol. 11, no. 4, pp. 1-28, 2020, doi: 10.3390/INFO11040207.

[2] M. Heron and V. Statistics, "National Vital Statistics Reports Deaths: Leading Causes for 2017," *National Center for Health Statistics*, vol. 68, no. 6, 2019.

[3] E. J. Benjamin, P. Muntner, and A. Alonso, "Heart Disease and Stroke Statistics-2019 Update: A Report From the American Heart Association," *Circulation*, vol. 139, no. 10, pp. e56-e528, 2019, doi: 10.1161/CIR.0000000000000659.

[4] C. Krittanawong *et al.*, "Deep learning for cardiovascular medicine: A practical primer," *European Heart Journal*, vol. 40, no. 25, pp. 2058-2073, Feb. 2019, doi: 10.1093/eurheartj/ehz056.

[5] S. Krishnan, P. Magalingam, and R. B. Ibrahim, "Advanced recurrent neural network with tensorflow for heart disease prediction," *International Journal of Advanced Science and Technology*, vol. 29, no. 5, pp. 966-977, 2020.

[6] D. Ben-Israel *et al.*, "The impact of machine learning on patient care: A systematic review," *Artificial Intelligence in Medicine*, vol. 103, Mar. 2020, Art. no. 101785, doi: 10.1016/j.artmed.2019.101785.

[7] R. Vaishya, M. Javaid, I. H. Khan, and A. Haleem, "Artificial Intelligence (AI) applications for COVID-19 pandemic," *Diabetes and Metabolic Syndrome: Clinical Research and Reviews*, vol. 14, no. 4, pp. 337-339, 2020, doi: 10.1016/j.dsx.2020.04.012.

[8] S. Mohan, C. Thirumalai, and G. Srivastava, "Effective Heart Disease Prediction Using Hybrid Machine Learning Techniques," in *IEEE Access*, vol. 7, pp. 81542-81554, 2019, doi: 10.1109/ACCESS.2019.2923707.
[9] A. Dutta, T. Batabyal, M. Basu, and S. T. Acton, "An efficient convolutional neural network for coronary heart disease prediction," *Expert System Applications*, vol. 159, 2020, Art. no. 113408, doi: 10.1016/j.eswa.2020.113408.
[10] R. Miikkulainen *et al.*, "Chapter 15-Evolving Deep Neural Networks," *Artificial Intelligence in the Age of Neural Networks and Brain Computing*, 2019, pp. 293-312, doi: 10.1016/B978-0-12-815480-9.00015-3.
[11] D. Shetty, C. A. Harshavardhan, M. J. Varma, S. Navi, and M. R. Ahmed, "Diving Deep into Deep Learning: History, Evolution, Types and Applications," *International Journal of Innovative Technology and Exploring Engineering (IJITEE)*, vol. 9, no. 3, pp. 2835-2846, 2020, doi: 10.35940/ijitee.a4865.019320.
[12] T. Araujo, N. Helberger, S. Kruikemeier, and C. H. de Vreese, "In AI we trust? Perceptions about automated decision-making by artificial intelligence," *AI and Society*, vol. 35, pp. 611-623, 2020, doi: 10.1007/s00146-019-00931-w.
[13] R. Zhao, R. Yan, Z. Chen, K. Mao, P. Wang, and R. X. Gao, "Deep learning and its applications to machine health monitoring," *Mechanical Systems Signal Processing*, vol. 115, pp. 213-237, 2019, doi: 10.1016/j.ymssp.2018.05.050.
[14] B. S. Babu, A. Suneetha, G. C. Babu, Y. J. N. Kumar, and G. Karuna, "Medical disease prediction using grey wolf optimization and auto encoder based recurrent neural network," *Periodicals of Engineering and Natural Sciences*, vol. 6, no. 1, pp. 229-240, 2018, doi: 10.21533/pen.v6i1.286.
[15] N. Singh, "A Modified Variant of Grey Wolf Optimizer," *int J Sci Technol Sci Iran*, 2018, doi: 10.24200/sci.2018.50122.1523.
[16] Zhi-Jun Teng, Jin-Ling Lv, and Li-Wen. Guo, "An improved hybrid grey wolf optimization algorithm," *Soft Computing*, vol. 23, no. 15, pp. 6617-6631, 2019, doi: 10.1007/s00500-018-3310-y.
[17] F. Jiang *et al.*, "Artificial intelligence in healthcare: Past, present and future," *Stroke Vascular Neurology*, vol. 2, no. 4, pp. 230-243, 2017, doi: 10.1136/svn-2017-000101.
[18] V. V. Ramalingam, A. Dandapath, and M. K. Raja, "Heart disease prediction using machine learning techniques: A survey," *International Journal of Engineering & Technology*, vol. 7, no. 2.8, pp. 684-687, 2018, doi: 10.14419/ijet.v7i2.8.10557.
[19] I. Javid, A. K. Z. Alsaedi, and R. Ghazali, "Enhanced accuracy of heart disease prediction using machine learning and recurrent neural networks ensemble majority voting method," *International Journal of Advanced Computer Science and Applications (IJACSA)*, vol. 11, no. 3, pp. 540-551, 2020, doi: 10.14569/ijacsa.2020.0110369.
[20] F. Farzadfar, "Cardiovascular disease risk prediction models: challenges and perspectives," *The Lancet Global Health*, vol. 7, no. 10, pp. e1288-e1289, 2019, doi: 10.1016/S2214-109X(19)30365-1.
[21] P. P. Prasad and F. S. Francis, "Medical Data Classification Based on SMOTE and Recurrent Neural Network," *International Journal of Engineering and Advanced Technology (IJEAT)*, vol. 9, no. 3, Jun. 2020, doi: 10.35940/ijeat.C5444.029320.
[22] D. Acemoglu and P. Restrepo, "The wrong kind of AI? Artificial intelligence and the future of labour demand," *Cambridge Journal of Regions, Economy and Society*, vol. 13, no. 1, pp. 25-35, Dec. 2019, doi: 10.1093/cjres/rsz022.
[23] K. Kersting, "Machine Learning and Artificial Intelligence: Two Fellow Travelers on the Quest for Intelligent Behavior in Machines," *Frontiers Big Data*, vol. 1, pp. 1-4, Nov. 2018, doi: 10.3389/fdata.2018.00006.
[24] M. Chen, U. Challita, W. Saad, C. Yin, and M. Debbah, "Artificial Neural Networks-Based Machine Learning for Wireless Networks: A Tutorial," *IEEE Commun. Surv. Tutorials*, vol. 21, no. 4, pp. 3039-3071, 2019, doi: 10.1109/COMST.2019.2926625.
[25] O. M. Al-Mubayyed, B. S. Abu-Nasser, and S. S. Abu-Naser, "Predicting Overall Car Performance Using Artificial Neural Network," *International Journal Academy Applied Research*, vol. 3, no. 1, pp. 1-5, 2019. [Online]. Available: http://www.ijeais.org/ijaar.
[26] N. S. R. Pillai, K. K. Bee, and J. Kiruthika, "Prediction Of Heart Disease Using RNN Algorithm," *International Research Journal of Engineering and Technology (IRJET)*, vol. 6, no. 3, pp. 4452-4458, 2019.
[27] S. Gao, Y. Zheng, and X. Guo, "Gated recurrent unit-based heart sound analysis for heart failure screening," *Biomedical Engineering Online*, vol. 19, no. 1, pp. 1-17, 2020, doi: 10.1186/s12938-020-0747-x.
[28] J. Chen, H. Jing, Y. Chang, and Q. Liu, "Gated recurrent unit based recurrent neural network for remaining useful life prediction of nonlinear deterioration process," *Reliability Engineering and System Safety*, vol. 185, pp. 372-382, 2019, doi: 10.1016/j.ress.2019.01.006.
[29] D. Grattarola and C. Alippi, "Graph Neural Networks in Tensorflow and Keras with Spektral," *arXiv preprint arXiv:2006.12138*, 2020.
[30] Y. Li, C. Huang, L. Ding, Z. Li, Y. Pan, and X. Gao, "Deep learning in bioinformatics: Introduction, application, and perspective in the big data era," *Methods*, vol. 166, pp. 4-21, Aug. 2019, doi: https://doi.org/10.1016/j.ymeth.2019.04.008.
[31] M. Abadi *et al.*, "TensorFlow: A System for Large-Scale Machine Learning," in *12th {USENIX} Symposium on Operating Systems Design and Implementation ({OSDI} 16)*, Nov. 2016, pp. 265-283, [Online]. Available: https://www.usenix.org/conference/osdi16/technical-sessions/presentation/abadi.
[32] F. Ali *et al.*, "A smart healthcare monitoring system for heart disease prediction based on ensemble deep learning and feature fusion," *Information Fusion*, vol. 63, pp. 208-222, 2020, doi: 10.1016/j.inffus.2020.06.008.

[33] L. Ali, A. Rahman, A. Khan, M. Zhou, A. Javeed, and J. A. Khan, "An Automated Diagnostic System for Heart Disease Prediction Based on ${\chi^{2}}$ Statistical Model and Optimally Configured Deep Neural Network," in *IEEE Access*, vol. 7, pp. 34938-34945, 2019, doi: 10.1109/ACCESS.2019.2904800.

[34] S. K. Bandyopadhyay, "Stacked Bi-directional LSTM Layer Based Model for Prediction of Possible Heart Disease during Lockdown Period of COVID-19," *J. Adv. Res. Med. Sci. Technol.*, vol. 07, no. 02, pp. 10–14, 2020, doi: 10.24321/2394.6539.202006.

[35] A. Kishore, A. Kumar, K. Singh, M. Punia, and Y. Hambir, "Heart Attack Prediction Using Deep Learning," *Heart*, vol. 5, no. 4, pp. 4420-4423, 2018.

[36] S. Dutta and S. K. Bandyopadhyay, "Early Detection of Heart Disease Using Gated Recurrent Neural Network," vol. 3, no. 1, pp. 8-15, 2020.

[37] R. Rustogi and A. Prasad, "Swift Imbalance Data Classification using SMOTE and Extreme Learning Machine," *2019 International Conference on Computational Intelligence in Data Science (ICCIDS)*, 2019, pp. 1-6, doi: 10.1109/ICCIDS.2019.8862112.

[38] J. Sun, H. Li, H. Fujita, B. Fu, and W. Ai, "Class-imbalanced dynamic financial distress prediction based on Adaboost-SVM ensemble combined with SMOTE and time weighting," *Information Fusion*, vol. 54, pp. 128-144, 2020, doi: 10.1016/j.inffus.2019.07.006.

[39] N. V. Ravindhar, K. Anand, S. Hariharan, Ragavendran, and S. G. Winster, "Intelligent diagnosis of cardiac disease prediction using machine learning," *Int. J. Innov. Technol. Explor. Eng.*, vol. 8, no. 11, pp. 1417-1421, 2019, doi: 10.35940/ijitee.J9765.0981119.