ORIGINAL RESEARCH

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Heart Disease Prediction Based on Age Detection Using Logistic Regression over Random Forest

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ABSTRACT

Aim: To improve the accuracy in Heart Disease Prediction using Logistic Regression and Random Forest. **Materials and Methods:** This study contains 2 groups i.e Logistic Regression and Random Forest. Each group consists of a sample size of 10 and the study parameters include alpha value 0.01, beta value 0.2, and the Gpower value of 0.8. **Results:** The Logistic Regression achieved improved accuracy of 91.60 then the Random Forest in Heart Disease Prediction. The statistical significance difference is 0.01 ($p<0.05$). **Conclusion:** The Logistic Regression model is significantly better than the Random Forest in Heart Disease Prediction. It can be also considered a better option for Heart Disease Prediction. deviation (0.08600,0.09333)

Keywords

Logistic Regression, Novel Random Forest, Heart disease prediction, Accuracy, Machine Learning.

Imprint

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INTRODUCTION

Heart Complaint depicts a scope of conditions that influence your heart. Heart conditions incorporate Blood vessel grievances, like coronary interstate complaints(Che et al. 2021). Heart-meter issues (arrhythmias) Heart curses you are brought into the world with (normal heart scars) Coronary interstate objections, arrhythmia, heart slant grievances, and cardiovascular breakdown are the four most normal sorts of heart protests. The significant test that the Healthcare assiduity faces by and by is the prevalence of establishments. Diagnosing the grumbling properly and outfitting powerful treatment to cases will characterize the nature of administration. Unfortunate assessment causes appalling results that aren't acknowledged(El-Hasnony et al. 2022). The significant test that the Healthcare assiduity faces by and by is the prevalence of establishments. Diagnosing the grumbling properly and outfitting compelling treatment to cases will characterize the nature of administration. Unfortunate assessment causes awful outcomes that aren't acknowledged(Quan et al. 2022). It's vital to diagnose the complaint at an early stage(Sharma et al. 2022). The application of this paper presents a comparable utilization of coronary illness expectations. The EHDPS predicts the likelihood of patients getting coronary sickness. It engages basic data, eg, associations between clinical components associated with coronary ailment and models, to be spread out ns, to be laid out

In Heart Disease Prediction using Logistic Regression related articles around 80 in IEEE Digital Xplore and 88 of this research is to improve the performance accuracy of heart disease prediction. Many studies have been conducted that result in restrictions on feature selection for science Direct There's been a lot of research that contains Machine data learning approaches authors like(Krishnamoorthi et al. 2022). In this paper, we develop a heart disease prediction system that can assist medical professionals in predicting heart disease status(Huang et al. 2022). There's been a lot of research into heart disease prediction that contains data learning approaches(Wan et al. 2021). The paper focuses on the accuracy of evaluating Heart Disease Prediction in each of the 50 states using Classification Function Algorithms(CFA) and Long Short-Term Memory (LSTM), two different forecasting techniques developed and used to predict the accurate prediction of heart diseases(Forrest et al. 2022). The accurate prediction of the algorithm is used to get better accuracy. the given accuracy is predicted inaccuracyOur team has extensive knowledge and research experience that has translate into high quality publications(Chellapa et al. 2020; Lavanya, Kannan, and Arivalagan 2021; Raj R, D, and S 2020; Shilpa-Jain et al. 2021; S, R, and P 2021; Ramadoss, Padmanaban, and Subramanian 2022; Wu et al. 2020; Kalidoss, Umapathy, and Rani

Thirunavukkarasu 2021; Kaja et al. 2020; Antink et al. 2020; Paul et al. 2020; Malaikolundhan et al. 2020)

The exploration gap in Heart Disease Prediction is the vacuity of real-time data sets is limited and the delicacy to be better(Pičulin et al. 2022). The selection of the algorithm also plays a vital part in Heart Disease Prediction, Day by day the cases of heart diseases are increasing at a rapid rate and it's very important and concerning to predict any such diseases. This diagnosis is a difficult task i.e. it should be performed precisely and efficiently. The research paper mainly focuses on which patient is more likely to have heart disease based on various medical attributes. We prepared a heart disease prediction system to predict whether the patient is likely to be diagnosed with heart disease or not using the medical history of the patient. This exploration focuses on better accuracy in Heart Disease Prediction Using Logistic Regression over Random Forest.

MATERIALS AND METHODS

This work is carried out at Saveetha School of Engineering, Department of Information Technology in the Data Analytics Lab. The study consists of two sample groups i.eLogistic Regression and Random Forest. Each group consists of 10 samples with a pre-test power of 0.18. The sample size kept the threshold at 0.05, G power of 80%, confidence interval at 95%, and enrolment ratio at 1.

Data Preparation

To perform Heart Disease Prediction the real-time data sets used are heart data. The input data sets for the proposed work in heart data.csv were collected from GitHub.com ("Git Hub: Your Machine Learning and Data Science Community"). The data sets consist of the attributes are age, chest pain type, and resting blood pressure are dependent attributes, and fasting blood sugar, resting electrocardiographic results, and maximum heart rate achieved are independent attributes that do not affect the results removed from the. csv file.

Logistic Regression

Logistic Regression analysis is used to prognosticate the value of a variable grounded on the value of another variable. The variable you want to prognosticate is called the dependent variable. Medical biographies of diseases similar to coitus, age, hypertension, blood sugar, and other symptoms are used for vaccination. The model is designed to prognosticate the possibility of cases of heart disease. The variable you're using to prognosticate the other variable's value is called the independent variable. Logistic Regression analysis is used to prognosticate the value of a variable grounded on the value of another variable. The variable you want to prognosticate is called the dependent variable. The variable you're using to prognosticate the other variable's value is called the independent variable. The logistic retrogression algorithm is represented in the graphs showing the difference between the attributes. From the training data, we've to estimate the stylish and approximate measure and represent it

Logistic retrogression is used to prognosticate the class (or order) of individualities grounded on one or multiple predictor variables (x). It's used to model a double outgrowth, that's available, which can have only two possible values 0 or 1, yes or no, diseased or non-diseased is Calculated using equation 1.

$$\mathbf{P/\ (1\text{-}P) = eY - eq} \qquad (1)$$

From this p-value is planted out. This gives the probability or chance for the individual to have a coronary heart complaint

The exploration gap in Heart Disease Prediction Is the vacuity of real-time data sets is limited and the delicacy to be better. The selection of the algorithm also plays a vital part in Heart Disease Prediction, So, this exploration focuses on better delicacy in Heart Disease Prediction UsingLogistic Regression over Random Forest. Pseudocode and Accuracy Values for the regression model has mentioned in Table 1 and Table 3

Random Forests Regression

The Random timber classifier creates a set of Random Forests from an aimlessly named subset of the training set. It's principally a set of Random Forests (DT) from an aimlessly named subset of the training set and also collects the votes from different novel random Forests to decide the final vaticination

For illustration, the vaccination for trees 1 and 2 is apple. Another Random Forest (n) has predicted banana as the outgrowth. The arbitrary timber classifier collects the maturity voting to give the final vaccination. Medical lives of diseased analogs such as commerce, age, hypertension, blood sugar, and other symptoms are used for prophecy. The model is designed to predict the possibility of cases getting heart complaints. Logistic Regression analysis is used to predict the value of a variable predicated on the value of another variable. The variable you want to predict is called the dependent variable. The variable you are using to predict the other variable's value is called the independent variable x1.

$$x2 = nm.\ mesh\ grid \\ (nm.arrange\ (\ launch = xset\ (,0). \\ min\ ()\text{-}1,\ stop = y\ set\ (,0). \tag{2}$$

Random Forest Regression is a supervised literacy algorithm that uses the ensemble literacy system for Regression The ensemble literacy system is a fashion that combines prognostications from multiple machine learning algorithms to make a more accurate vaccination than a single model is Direct Regression model is known as Random Forest Regression Pseudocode and Accuracy Values for the regression model are mentioned in Table 2 and Table 4.

Table 1

Pseudocode for Logistic Regression

Input: Heart Symptoms dataset records
1. Import the required packages.
2. Convert the Data Sets into numerical values after the extraction feature.
3. Assign the data to X_train, y_train, X_test, and y_test variables.
4. Using the train_test_split() function, pass the training and testing variables.
5. Give test_size and the random_state as parameters for splitting the data using the Logistic training model.
6. Compiling the model using metrics as accuracy
7. Calculate the accuracy of the model.
OUTPUT: Accuracy

Table 2

Pseudocode for Random Forest

Input: Heart Symptoms dataset records
1. Import the required packages.
2. Convert the Data Sets into numerical values after the extraction feature.
3. Assign the data to X_train, y_train, X_test, and y_test variables.
4. Using the train_test_split() function, pass the training and testing variables.
5. Give test_size and the random_state as parameters for splitting the data using Random Forest Model
6. Compiling the model using metrics as accuracy.
7. Evaluate the output using X_test and y_test function
8. Get the accuracy of the model.
OUTPUT: Accuracy

Table 3

Accuracy of Heart Disease Prediction Using Logistic Regression

Model Sample Size	Accuracy
Training Split- 71%, Test Split -29%	98.45
Training Split- 72%, Test Split -28%	98.12
Training Split- 73%, Test Split -27%	97.81
Training Split- 74%, Test Split -26%	97.34
Training Split- 75%, Test Split -25%	97.15
Training Split- 76%, Test Split -24%	96.74
Training Split- 77%, Test Split -23%	96.45
Training Split- 78%, Test Split -22%	95.65
Training Split- 79%, Test Split -21%	94.67
Training Split- 80%, Test Split -20%	94.33

Table 4

Accuracy of Heart Disease Prediction using Novel Random Forest

Model Sample Size	Accuracy
Training Split- 71%, Test Split -29%	69.72
Training Split- 72%, Test Split -28%	68.45
Training Split- 73%, Test Split -27%	67.38
Training Split- 74%, Test Split -26%	66.58
Training Split- 75%, Test Split -25%	65.81
Training Split- 76%, Test Split -24%	64.18
Training Split- 77%, Test Split -23%	63.28
Training Split- 78%, Test Split -22%	62.48
Training Split- 79%, Test Split -21%	61.85
Training Split- 80%, Test Split -20%	60.28

Statistical Analysis

The minimum requirement to run the software used here is Intel Core i3 Dual-Core CPU clocked @3.2 GHz,4GB or above memory of RAM, more than 512MB space is required and Software specification includes Windows 7/8/10/11 Professional 64-bit OS, Jupyter Notebook Version 6.30 with Python3, and MS-Office. Statistical Package for the Social Sciences Version 26 software tool was used for statistical analysis. An independent sample T-test was conducted for accuracy. Standard deviation and standard mean errors were also calculated using the SPSS Software tool. The significance values of proposed and existing algorithms contain group statistical values of proposed and existing algorithms.Descriptive Statistic analysis mentioned in Table 5

RESULTS

The group statistical analysis of the two groups shows logistic Regression (group 1) has more mean accuracy than Random Forest (group 2) and the standard error mean is slightly less than Logistic Regres-

Table 5. Descriptive Statistic analysis, representing Logistic Regression and Novel Random Forest

Algorithm	N	Minimum	Maximum	Mean	Std. Deviation
Group1	20	1.00	2.00	1.5000	.51299
Accuracy	20	79.48	91.89	83.3670	8.78744
Error	20	8.11	29.64	16.6330	8.78744
Valid N (listwise)	20				

sion. The logistic Regression scored an accuracy of 91.60% and Random Forest scored 69.72%. The accuracies are recorded by testing the algorithms with 10 different sample sizes and the average accuracy is calculated for each algorithm.

In SPSS, the datasets are prepared using 10 as a sample size for logistic Regression and Random Forest. Group is given as a grouping variable and Heart Disease is given as the testing variable. Group is given as 1 for Logistic Regression and 2 for Random Forest. Descriptive Statistics is applied for the dataset in SPSS and shown in Table 6, Group statistics is shown in Table 7, and Two Independent Sample T-Tests in Table 8.

Table 6

Group Statistic analysis, representing Logistic Regression (mean accuracy 91.65%, standard deviation 0.08600,0.09333) and Random Forest(mean accuracy 91.59%, standard deviation 0.08600,0.09333)

	Algorithm	N	Mean	Std. Deviation	Std.Error Mean
Accuracy	Logistic Regression	10	91.6730	.14622	.04624
	Random Forest	10	65.0010	3.07643	3.07643
Error	Logistic Regression Error	10	8.3270	.14622	.04624
	Random Forest	10	15.8680	.13442	.99119

Table 7

Independent Sample Tests results with a confidence interval of 95% and a level of significance of 0.05 (Logistic Regression appears to perform significantly better than novel Random Forest with the value of p=0.18).

Accuracy	Levene's Test for Equality of Variances		T-test for Equality of Means						
	F	Sig.	t	df	Sig	Mean Difference	Std. Error Difference	95% Conf. Interval Lower	95% Conf. Interval Upper
Accuracy Equal variances assumed Equal variances not assumed	29.74	.001	-1.694 -1.694	18 17.881	.107 .108	.06800 .06800	.04013 .04013	-.01632 -.01636	.15232 .15236
Error Equal variances assumed Equal variances not assumed	29.74	.001	-1.694 -1.694	18 17.881	.107 .108	-.06800 -.06800	.04013 .04013	-.15232 -.15236	.01632 .01636

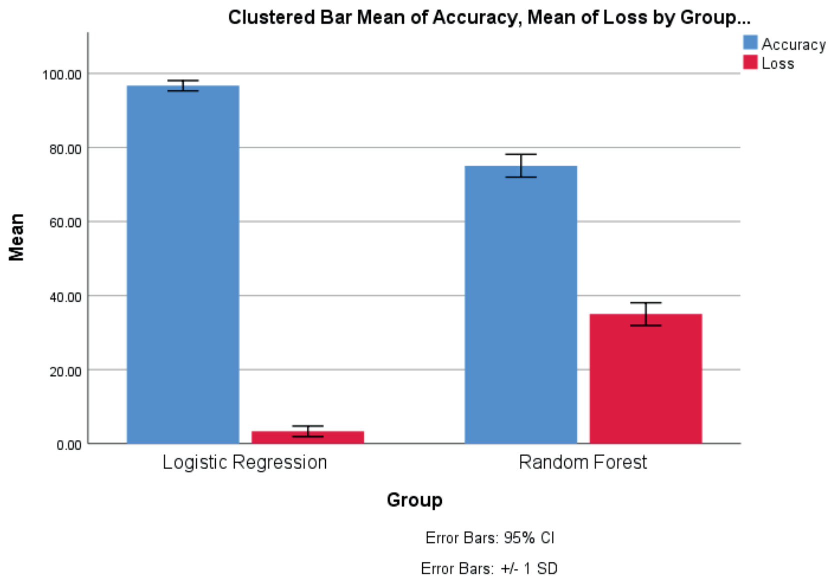

Fig. 1. Comparison of Logistic Regression and Random Forest in terms of accuracy. The mean accuracy of Logistic Regression is greater than Novel Random Forest and the standard deviation is also slightly higher than Random Forest. X-axis: Logistic Regression vs Random Forest. Y-axis: Mean accuracy of detection + 1 SD.

DISCUSSION

From the results of this study, Logistic Regression is proved to be having better accuracy than the Random Forest model. Logistic Regression has an accuracy of 91.60% whereas Random Forest has an accuracy of 69.72%. The group statistical analysis on the two groups shows that logistic Regression (group 1) has more mean accuracy than Random Forest (group 2) and the standard error mean including the standard deviation mean is slightly less than Logistic Regression. The application of this paper presents a comparable utilization of coronary illness expectations. The EHDPS predicts the likelihood of patients getting coronary sickness. It engages basic data, eg, associations between clinical components associated with coronary ailment and models, to be spread out ns, to be laid out

Heart Disease Prediction using Machine learning is now becoming widely used as a methodology(Park et al. 2021). Citizens have employed machine learning algorithms to address problems based on their own industry data(Ren, Wang, and Luo 2021). Industry professionals have used machine learning to perform classification jobs and diagnose malfunctions(Asiimwe et al. 2022). People in the field of business frequently used machine learning algorithms in financial research A Khemphila, V Boonjing – 2010. The paper focuses on the accuracy of evaluating housing prices in each of the 50 states using Classification Function Algorithms(CFA) and Long Short-Term Memory (LSTM), two different forecasting techniques developed and motivated by Raftery, Karny, and Ettler (2010) and Koop and Korobilis, correspondingly (2012). The strategies take into account all of the K = 2m distinct model combinations in each time period t when there are m predictors available.

The limitation of the proposed work is due to inconsistent data and difficulty in getting the right datasets for analysis(Wang et al. 2021). Future work can be concentrated on effective data preprocessing techniques and the usage of ensemble machine learning algorithms can be focused.

CONCLUSION

Based on the experimental results Logistic Regression has been proved to predict Heart Disease more significantly than novel random Forest. The quality of datasets formed with value and accuracy is improved in detecting heart diseases. It can be used in predicting heart diseases in the future.

DECLARATIONS

Conflicts of Interest

No conflicts of interest in this manuscript.

Author Contributions

Author CBMK was involved in data collection, data analysis, data extraction, and manuscript writing. Author AK was involved in the conceptualization, data validation, and critical review of the manuscript.

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REFERENCES

1. Antink, Christoph Hoog, Joana Carlos Mesquita Ferreira, Michael Paul, Simon Lyra, Konrad Heimann, Srinivasa Karthik, Jayaraj Joseph, et al. 2020. "Fast Body Part Segmentation and Tracking of Neonatal Video Data Using Deep Learning." Medical & Biological Engineering & Computing 58 (12): 3049–61.
2. Asiimwe, Innocent G., Marc Blockman, Karen Cohen, Clint Cupido, Claire Hutchinson, Barry Jacobson, Mohammed Lamorde, et al. 2022. "Stable Warfarin Dose Prediction in Sub-Saharan African Patients: A Machine-Learning Approach and External Validation of a Clinical Dose-Initiation Algorithm." CPT: Pharmacometrics & Systems Pharmacology 11 (1): 20–29.
3. Chellapa, L. R., S. Rajeshkumar, M. I. Arumugham, and S. R. Samuel. 2020. "Biogenic Nanoselenium Synthesis and Evaluation of Its Antimicrobial, Antioxidant Activity and Toxicity." Bioinspired Biomimetic and Nanobiomaterials, July, 1–6.
4. El-Hasnony, Ibrahim M., Omar M. Elzeki, Ali Alshehri, and Hanaa Salem. 2022. "Multi-Label Active Learning-Based Machine Learning Model for

Heart Disease Prediction." Sensors 22 (3). https://doi.org/10.3390/s22031184.
5. Forrest, Mekayla, Sophia Bourgeois, Émilie Pichette, Sarah Caughlin, Alvin Kuate Defo, Lindsay Hales, Christopher Labos, and Stella S. Daskalopoulou. 2022. "Arterial Stiffness Measurements in Pregnancy as a Predictive Tool for Hypertensive Disorders of Pregnancy and Preeclampsia: Protocol for a Systematic Review and Meta-Analysis." European Journal of Obstetrics & Gynecology and Reproductive Biology: X 13 (January): 100141.
6. Huang, Weiting, Tan Wei Ying, Woon Loong Calvin Chin, Lohendran Baskaran, Ong Eng Hock Marcus, Khung Keong Yeo, and Ng See Kiong. 2022. "Application of Ensemble Machine Learning Algorithms on Lifestyle Factors and Wearables for Cardiovascular Risk Prediction." Scientific Reports 12 (1): 1033.
7. Kaja, Rekha, Anandh Vaiyapuri, Mohamed Sherif Sirajudeen, Hariraja Muthusamy, Radhakrishnan Unnikrishnan, Mohamed Waly, Samuel Sundar Doss Devaraj, Mohamed Kotb Seyam, and Gopal Nambi S. 2020. "Biofeedback Flutter Device for Managing the Symptoms of Patients with COPD." Technology and Health Care: Official Journal of the European Society for Engineering and Medicine 28 (5): 477–85.
8. Kalidoss, Ramji, Snekhalatha Umapathy, and Usha Rani Thirunavukkarasu. 2021. "A Breathalyzer for the Assessment of Chronic Kidney Disease Patients' Breathprint: Breath Flow Dynamic Simulation on the Measurement Chamber and Experimental Investigation." Biomedical Signal Processing and Control 70 (September): 103060.
9. Krishnamoorthi, Raja, Shubham Joshi, Hatim Z. Almarzouki, Piyush Kumar Shukla, Ali Rizwan, C. Kalpana, and Basant Tiwari. 2022. "A Novel Diabetes Healthcare Disease Prediction Framework Using Machine Learning Techniques." Journal of Healthcare Engineering 2022 (January): 1684017.
10. Lavanya, M., P. Muthu Kannan, and M. Arivalagan. 2021. "Lung Cancer Diagnosis and Staging Using Firefly Algorithm Fuzzy C-Means Segmentation and Support Vector Machine Classification of Lung Nodules." International Journal of Biomedical Engineering and Technology 37 (2): 185.
11. Malaikolundhan, Harikrishna, Gowsik Mookkan, Gunasekaran Krishnamoorthi, Nirosha Matheswaran, Murad Alsawalha, Vishnu Priya Veeraraghavan, Surapaneni Krishna Mohan, and Aiting Di. 2020. "Anticarcinogenic Effect of Gold Nanoparticles Synthesized from Albizia Lebbeck on HCT-116 Colon Cancer Cell Lines." Artificial Cells, Nanomedicine, and Biotechnology 48 (1): 1206–13.
12. Park, Boyoung, Yeol Kim, Jaeho Lee, Nayoung Lee, and Seung Hun Jang. 2021. "Risk-Based Prediction Model for Selecting Eligible Population for Lung Cancer Screening among Ever Smokers in Korea." Translational Lung Cancer Research 10 (12): 4390–4402.
13. Paul, M., S. Karthik, J. Joseph, M. Sivaprakasam, J. Kumutha, S. Leonhardt, and C. Hoog Antink. 2020. "Non-Contact Sensing of Neonatal Pulse Rate Using Camera-Based Imaging: A Clinical Feasibility Study." Physiological Measurement 41 (2): 024001.
14. Pičulin, Matej, Tim Smole, Bojan Žunkovič, Enja Kokalj, Marko Robnik-Šikonja, Matjaž Kukar, Dimitrios I. Fotiadis, et al. 2022. "Disease Progression of Hypertrophic Cardiomyopathy: Modeling Using Machine Learning." JMIR Medical Informatics 10 (2): e30483.
15. Quan, Ruilin, Shian Huang, Lingpin Pang, Jieyan Shen, Weifeng Wu, Fangming Tang, Xiulong Zhu, et al. 2022. "Risk Prediction in Pulmonary Hypertension due to Chronic Heart Failure: Incremental Prognostic Value of Pulmonary Hemodynamics." BMC Cardiovascular Disorders 22 (1): 56.
16. Raj R, Kathiswar, Ezhilarasan D, and Rajeshkumar S. 2020. "β-Sitosterol-Assisted Silver Nanoparticles Activates Nrf2 and Triggers Mitochondrial Apoptosis via Oxidative Stress in Human Hepatocellular Cancer Cell Line." Journal of Biomedical Materials Research. Part A 108 (9): 1899–1908.
17. Ramadoss, Ramya, Rajashree Padmanaban, and Balakumar Subramanian. 2022. "Role of Bioglass in Enamel Remineralization: Existing Strategies and Future Prospects-A Narrative Review." Journal of Biomedical Materials Research. Part B, Applied Biomaterials 110 (1): 45–66.
18. Ren, Xuehan, Jue Wang, and Sheng Luo. 2021. "Dynamic Prediction Using Joint Models of Longitudinal and Recurrent Event Data: A Bayesian Perspective." Biostatistics & Epidemiology 5 (2): 250–66.
19. Sharma, Divya, Neta Gotlieb, Michael E. Farkouh, Keyur Patel, Wei Xu, and Mamatha Bhat. 2022. "Machine Learning Approach to Classify Cardiovascular Disease in Patients With Nonalcoholic Fatty Liver Disease in the UK Biobank Cohort." Journal of the American Heart Association 11 (1): e022576.
20. Shilpa-Jain, D. P., Jogikalmat Krithikadatta, Dinesh Kowsky, and Velmurugan Natanasabapathy.

2021. “Effect of Cervical Lesion Centered Access Cavity Restored with Short Glass Fibre Reinforced Resin Composites on Fracture Resistance in Human Mandibular Premolars- an in Vitro Study.” Journal of the Mechanical Behavior of Biomedical Materials 122 (October): 104654.

21. S, Sudha, Kalpana R, and Soundararajan P. 2021. “Quantification of Sweat Urea in Diabetes Using Electro-Optical Technique.” Physiological Measurement 42 (9). https://doi.org/10.1088/1361-6579/ac1d3a.

22. Wan, Chuanqi, Chen Zhu, Gulei Jin, Min Zhu, Junyi Hua, and Yuzhou He. 2021. “Analysis of Gut Microbiota in Patients with Coronary Artery Disease and Hypertension.” Evidence-Based Complementary and Alternative Medicine: eCAM 2021 (December): 7195082.

23. Wang, Guan, Yanbo Zhang, Sijin Li, Jun Zhang, Dongkui Jiang, Xiuzhen Li, Yulin Li, and Jie Du. 2021. “A Machine Learning-Based Prediction Model for Cardiovascular Risk in Women With Preeclampsia.” Frontiers in Cardiovascular Medicine 8 (October): 736491.

24. Wu, Shuang, Shanmugam Rajeshkumar, Malini Madasamy, and Vanaja Mahendran. 2020. “Green Synthesis of Copper Nanoparticles Using Cissus Vitiginea and Its Antioxidant and Antibacterial Activity against Urinary Tract Infection Pathogens.” Artificial Cells, Nanomedicine, and Biotechnology 48 (1): 1153–58.