Proceedings of the International Conference on Sustainable Computing and Data Communication Systems (ICSCDS-2022)
IEEE Xplore Part Number: CFP22AZ5-ART; ISBN: 978-1-6654-7884-7

Prediction of Heart Failure using Support Vector Machine compared with Decision Tree Algorithm for better Accuracy

Dharmish Dharmendra
Research Scholar,
Department of Computer Science and Engineering,
Saveetha School of Engineering,
Saveetha Institute of Medical and Technical Sciences,
Saveetha University, Chennai, Tamilnadu. India.
Pincode:602105.
dharmishdharmendra17@saveetha.com

Saravanan.M.S
Project guide, Corresponding author,
Department of Computer Science and Engineering,
Saveetha School of Engineering,
Saveetha Institute of Medical and Technical Sciences,
Saveetha University, Chennai, Tamilnadu. India.
Pincode:602105.
saravananms@saveetha.com

2022 International Conference on Sustainable Computing and Data Communication Systems (ICSCDS) | 978-1-6654-7884-7/22/$31.00 ©2022 IEEE | DOI: 10.1109/ICSCDS53736.2022.9760989

Abstract—***Heart attacks are frequently caused by partial or full blockages of the heart's arteries or veins, which restrict blood flow to or from the heart. The aim of this study is to develop the best categorization algorithm that will provide us with the most accurate forecasts. The Artificial Intelligence Laboratory of the Saveetha School of Engineering's Department of Computer Science and Engineering conducted this research. The classification algorithms utilised in this study are divided into two groups. The SVM and DT algorithms are in Groups 1 and 2, respectively with a g-power value of 80 percent and the heart images were collected from various web sources with recent study findings and threshold 0.05%, Confidence Interval 95% mean and standard deviation.The proposed system using SVM algorithm has achieved an improved accuracy of 72.54%, compared with DT algorithm with an accuracy of 70.32% with a significant value of two tailed tests is 0.027 (p<0.05) with 95% confidence interval. Prediction of heart failure using the SVM algorithm appears to be significantly better than the DT with improved accuracy.***

Keywords—Support Vector Machine, Decision Tree, Machine Learning, Accuracy, Efficiency, Innovative Disease Detection, Heart Images.

I. INTRODUCTION

The Support Vector Machine (SVM) algorithm looks to be much superior than the Decision Tree (DT) approach at predicting heart failure [1], [2]. Heart failure is on the rise globally, with an estimated 26 million instances recognised and millions more undiagnosed due to the ageing population, increased cardiovascular risk factors, and improved survival of cardiovascular illnesses. We need to focus primarily on the undiagnosed cases which are in the easy millions making it a very notable percentage in our society not only because of the number of lives at stake, but also because of the nature with which it impacts the community, being able to diagnose a prevailing issue of such size in an efficient manner becomes a priority. Previously, we only needed to look at patients who were impacted by age or other bodily weakening reasons because heart failure was mostly an indication of natural wear and tear of heart muscles [1]. This has changed drastically over the generations as there are several new factors that need to be looked into in determining the health of a person's heart. We live in a diluted watered down society where one person's problems can easily affect another but we can learn to make a connection in a diagnosis with similar data [3]. The importance of this research study is to target the various heart diseases and add them into the process of elimination with the help of an efficient classification algorithm infused with machine Learning [4]. There are few applications related to this research study that are all about heart related innovative diseases detections with different age factors [5]; [4]).

Related works of machine learning and artificial intelligence have been applied with reference to heart failure and the prediction of the heart failure pandemic. A research article by [6], they have used various classifiers such as SVM, DT, Logistic regression, SVM and MLP [7]. The objective is to compare the algorithms and find which is suited best to predict heart failure cases (Bhatia 2008). It is found that DT works well for smaller datasets [8]. Another research article by [9], has used DT, random forest and SVM to train their models. They have used a publicly available dataset which has 1140 X-ray images and 2400 CT-Scans [10] implemented a deep learning based SVM classifier for heart failure diagnosis [11]. It consists of three different binary decision 2 of 12 tree classifiers and each of them are trained using CNN based on a PyTorch frame. It can be used for screening patients for fast decision making. This research related work was presented and published in more than 42 indexed journals. We have collaborated with various authors across our institutions that has made us complete the project with ease and accuracy[12]–[28].

The accuracy percentage of the first and second SVMs are 98% and 80% respectively and the average accuracy of the third is 95% [29]. Another research paper has developed a prediction model using an AI technique which is based on a deep CNN to detect heart failure patients using chest X-Ray reports and chest CT scans [30], [31]. Most relevant article by [6] lacks accuracy score for the SVM classifier for predicting heart failure. Therefore the aim of this study is to increase the accuracy of predicting the likelihood of heart failure and improve the prediction model using the SVM.

II. MATERIALS AND METHODS

This research study was carried out at the Artificial Intelligence Laboratory, Department of Computer Science and Engineering, Saveetha School of Engineering, Chennai. This research study uses two groups of classification algorithms used for the study. Group 1 and Group 2 are the SVM algorithm and the DT algorithm respectively. Each sample size was predicted using the G-power tool with version 3.1.10 and resulting in 40 sample sizes with 80% of G-power values and the threshold two tailed significant value is set to 0.05 and the confidence interval as 95% [32].

The heart images dataset which is to be imputed for the proposed work is collected from kaggle website, one of the more popular online communities for data scientists and machine learning practitioners. It allows users to search and find different datasets that they require. It also provides a customizable personal jupyter notebook environment with a free online GPU. The dataset used here consists of 14 attributes and contains 12 features that can be used to predict the innovative disease detection with mortality by heart failure. The heart images dataset has 305 rows which consists of data for the symptoms that are related to heart failure which also includes duplicate, null and missing values. Cardiovascular diseases (CVDs) are the number 1 cause of death globally, taking an estimated 17.9 million lives each year, which accounts for 31% of all deaths worldwide.

The following pseudocode is used for the SVM algorithm to apply on the heart images dataset and also works with the tree model. The pseudocode will take the datasets as input and the final output of the pseudocode will be sent through the parameters accuracy and the classification. The SVM is a type of linear classifier that works on the premise of margin maximisation. They use structural risk minimization to increase the classifier's complexity in order to achieve outstanding generalisation performance for innovative disease detection.
Pseudocode of the SVM algorithm

```
candidateSV = { closest pair from opposite classes}

while there are violating points do
        Find a violator
        candidateSV = U candidate SVS violator
        if any ap < 0 due to addition of c to S then
        candidateSV = candidateSVP
        repeat till all such points are pruned
        end if
        end while
```

Pseudocode of the DT algorithm

DT falls under the category of supervised algorithms. DTs can be used for both classification and regression. In the classification DT the decision variable is categorical. For implementing a DT, the cost function used to evaluate the binary splits called the Gini Index should be calculated. The split creation is done with help of calculating the gini score, splitting the dataset and evaluating the all splits. Once this is done and the root node is created It can start building the tree by first deciding when to stop 3 of 12 the growth of the tree by creating the terminal node by setting the maximum tree depth and second, by using recursive splitting . The terminal node is used for the final prediction and recursive splitting is a method used to build the tree.

```
id3(examples,attributes)
Node = DecisionTreeNode(example)
Dictionary = summarizeExamples(examples,target attributes)
FOR key in dictionary:
If dictionary[key]==total number of examples
Node.label = key
Return node
If attributes is empty or number of examples < minimum allowed per branch:
Node.label = most common value in examples
Return node
bestA = the attribute with the most information gain
Node.decision = bestA
Each possible value v of bestA:
If subset is not empty:
Node.add branch(id3(subset,target attribute , attributes-bestA))
Return node
```

The algorithms are run with minimum requirements of hardware are Intel i3, 50-gigabyte hard disk capacity, and 4 gigabytes of Random Access Memory and the Software is required to run the algorithm on any windows operating system with python Anaconda Spyder with version 4.1.5. The independent sample T-Test was performed to compare the performances of the algorithm.The independent variable is Country attribute in the dataset and other 20 attributes such as fever, tiredness, difficulty in breathing etc are dependent variables for our study for heart failure Prediction. Finally, the results collected from the group one and group two algorithms will be applied to the Statistical Package for Social Sciences (SPSS) version 26.

III. RESULTS

The accuracy of the SVM and DT machine learning algorithms are compared with 10 samples by applying various 70% training and 30% testing datasets by varying the number of records in the dataset, and the results are shown in Table 1. The dataset has 305 rows, and the accuracy of both the DT and SVM algorithms is obtained for 10 samples (iterations).

TABLE 1. COMPARISON BETWEEN DT AND SVM ALGORITHM WITH N=10 SAMPLES OF THE DATASET WITH THE HIGHEST PERFORMANCE OF 18.25% AND 25.56% IN THE SAMPLE (WHEN N=1) USING THE DATASET SIZE = 200 AND THE 70% OF TRAINING AND 30% OF TESTING DATA.

Sample (N)	Dataset size / rows	DT Accuracy in %	SVM Accuracy in %
1	200	70.32	72.52
2	170	69.54	71.47
3	150	68.69	71.06
4	120	68.10	70.11
5	90	67.99	69.54
6	70	66.80	68.95
7	50	64.03	67.98
8	30	64.00	67.01
9	20	63.58	66.41
10	10	62.11	65.98

The frequency matrix of the symptoms experienced by the patient is shown in Fig. 1 and contrasted. The rest of the Electrocardiogram (ECG) comparison is displayed here as a symptom. The red signifies those who are at risk due to this one attribute, while the blue denotes those who are not at risk due to this one attribute; the values range from 0 to 200. The results of meal waste classification has accuracy for DT algorithm having 64.34% and KNN having 47.77% across the samples as shown in Fig. 1, from this we conclude that DT algorithm significantly reduces the error rate than KNN algorithm.

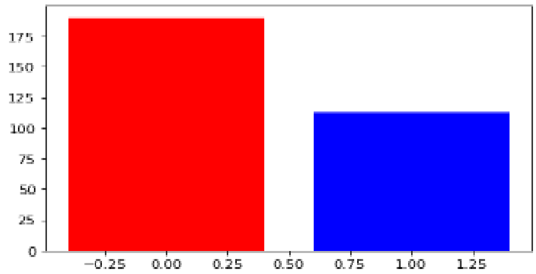

Fig. 1. Shows the Frequency matrix of the symptoms and the red denotes the people that are at risk and the blue are the ones not faced with a threat based on the inputs values range from 0 to 200.

Figure. 2 has the comparison of SVM algorithm and DT in terms of mean accuracy. The mean accuracy of SVM is better than DT and the standard deviation of SVM is slightly better than DT. X-axis: (GROUPS) SVM vs DT algorithm and Y axis: Mean accuracy of prediction ± 1 SD

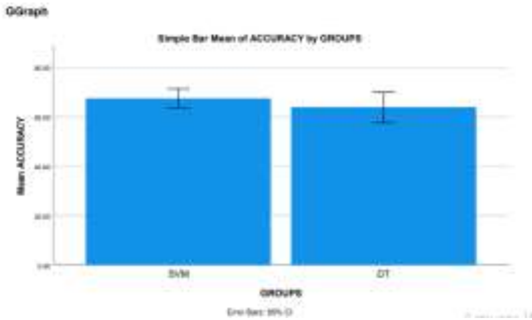

Fig. 2. Comparison of SVM algorithm and DT in terms of mean accuracy. The mean accuracy of SVM is better than DT and the standard deviation of SVM is slightly better than DT. X axis: SVM vs DT algorithm Y axis: Mean accuracy of prediction ± 1 SD

Figure. 3 shows the comparison of ROC AUC between SVM and DT. The red curve represents the SVM and the blue curve represents the DT. The ROC AUC score of SVM (75.5%) is better than DT (74.3%)

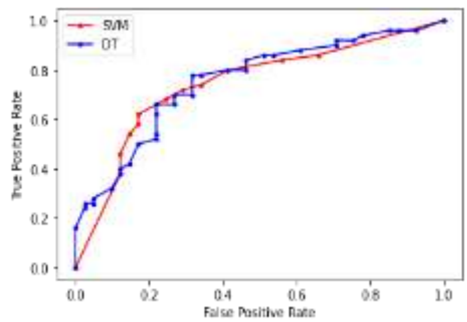

Fig. 3. Comparison of ROC AUC between SVM and DT. The red curve represents the SVM and the blue curve represents the DT. The ROC AUC score of SVM (75.5%) is better than DT (74.3%)

Figure. 4 shows the comparison of F1 score between SVM and DT. The red curve represents the SVM and the blue curve represents the DT. The ROC AUC score of SVM (74.7%) is better than DT (73.3%)

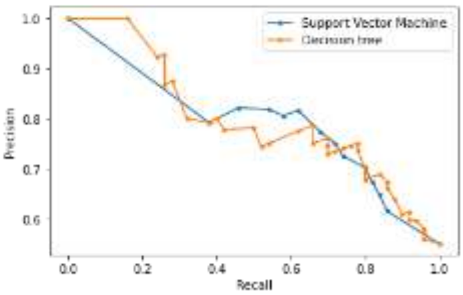

Fig. 4. Comparison of F1 score between SVM and DT. The red curve represents the SVM and the blue curve represents the DT. The ROC AUC score of SVM (74.7%) is better than DT (73.3%)

Figure. 5 has the comparison of accuracies between the SVM and the DT algorithm. The blue color curve represents the DT algorithm and the orange curve color represents the SVM algorithm, it shows that the DT is significantly better than the SVM algorithm.

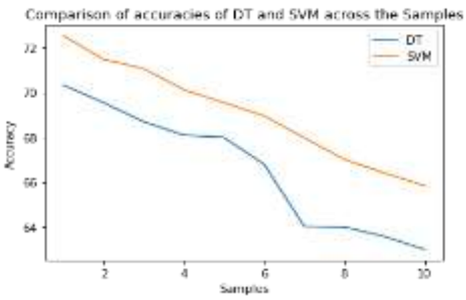

Fig. 5. Comparison of accuracies between SVM and DT. The blue color curve represents the DT algorithm having 70.32% and the orange curve color represents the SVM algorithm having 72.54%.

In Table 2 we observed after performing statistical analysis of 10 samples, DT obtained 6.218 standard deviations with 1.390 standard error while the SVM algorithm obtained 3.831 standard deviations with 0.856 standard error.

TABLE II. STATISTICAL RESULTS OF DT AND SVM ALGORITHMS. MEAN ACCURACY VALUE, STANDARD DEVIATION AND STANDARD ERROR MEAN FOR DT AND SVM ALGORITHMS ARE OBTAINED FOR 10 ITERATIONS. IT IS OBSERVED THAT THE SVM (67.53%) ALGORITHM PERFORMED BETTER THAN THE DT (63.76%) ALGORITHM.

Algorithms (Accuracy)	Sample (N)	Mean	Std Deviation	Std Error Mean
DT algorithm	10	63.76	6.218	1.390
SVM algorithm	10	67.53	3.831	0.856

The two tailed significant value (p=0.027) is smaller than 0.05 showed that our hypothesis holds a good value. For changes in the input values (independent variable) the corresponding output values (dependent variables) also change and it is depicted in Table 3. The output of group statistics independent samples is shown in Tables 2 and 3. Independent t-test was used to compare the accuracy of two algorithms and a statistically significant value p=0.027 was noticed, hence $p < 0.05$. The SVM model obtained 72.54% accuracy. When compared with the other algorithm's performance, the proposed SVM algorithm classifier achieved better performance than the DT algorithm.

TABLE III. THE INDEPENDENT SAMPLE T-TEST OF THE SIGNIFICANCE LEVEL DT AND SVM ALGORITHMS RESULTS WITH TWO TAILED SIGNIFICANT VALUES (P=0.027). THEREFORE BOTH THE DT AND THE SVM ALGORITHMS HAVE A SIGNIFICANCE LEVEL LESS THAN 0.05 WITH A 95 % CONFIDENCE INTERVAL.

Accuracy	Levene's Test for Equality of Variances		T-test of Equality of Means					95% of the confidence interval of the Difference	
	F	Sig.	t	df	Sig (2-tailed)	Mean Difference	Std Error Difference	Lower	Upper
Equal Variance Assumed	6.079	0.018	2.308	38.00	0.027	3.7695	1.6331	0.4634	7.0755
Equal Variance Not Assumed	-	-	2.308	31.69	0.027	3.7695	1.6331	0.4413	7.0976

The results of heart disease prediction have accuracy for SVM algorithm having 72.54% and DT having 70.32% across the samples as shown in Fig. 5, from this we conclude that SVM algorithm significantly reduces the error rate than DT algorithm.

IV. DISCUSSION

The SVM algorithm predicted heart failure rate with 72.54 percent accuracy, while the DT algorithm predicted heart failure rate with 70.32 percent accuracy, and we also determined that the SVM algorithm appears to be considerably better than the DT algorithm with (p=0.027). The computed value of p is 0.027 in Table 3, and the results corresponding to equal variances are used in the analysis.The fact that 't' is negative indicates that the SVM mean appears to be statistically bigger than the DT mean. As a result of this research, the SVM method appears to be much better than the DT algorithm (p=0.027). With enhanced accuracy, SVM appears to be substantially better than DT. The SVM classifier shows a significant difference in terms of accuracy score, speed and performance when compared to the DT classifier [3]. In the health-care industry, data mining is critical for innovative disease detections. A number of tests must be necessary from the patient for detecting an illness . Using data mining techniques, on the other hand, can reduce the number of tests required [32].

To support this work, a new classifier for heart disease prediction was utilised in a variety of techniques, including SVM and DT algorithms [33], as well as deep learning approaches, but we employed machine learning algorithms with 10 samples as input [10]. The other findings back up Naive Bayes algorithms with an accuracy of 82%, DT techniques with 75.21%, SVM methods with 76.7%, and the Inception SVM Model approach with 81 percent [11][33]; [11]. As a result, when compared to the performance of other algorithms, the suggested SVM method outperformed DT algorithms.

Other research findings, in contrast to this study, used face regions to predict facial expression, whereas we used the entire image of facial expression for analysis and only a small number of test cases in the operators. In this research study, we used a dataset with 305 rows and 10 different test cases. [10], [34]. One uses three distances, while the other uses five. We also included a weighted version, which is based on the average accuracy of each distance when used in the DT algorithm. With the UCI heart disease Cleveland data set, our ensemble provided an average accuracy of over 85% for all of the configurations and versions we evaluated but they were limited to using only a few test cases to achieve this accuracy [35]. This work combines the efficiency of the prominent classification approaches DT (DT) algorithm and Ant Colony Optimization (ACO). In the first stage, the test data is classified using the DT classification. In the second phase, where they feel DT is better than SVM, the ACO is used to initialise the population and search out the best solution [36]. Our university is dedicated to conducting high-quality, evidence-based research and has achieved success in a variety of areas [31].

This research study is limited to the SVM algorithm used to this heart pictures dataset with significant features such as ECG with case numbers, and it is also only relevant to heart disorders, and it compares the performance of these two groups for better outcomes. In future investigations, the new traits will be able to predict other diseases with sensitivity and specificity..

V. CONCLUSION

The unique heart pictures heart failure symptoms dataset is used in this study to predict heart failure using SVM and DT. The SVM classifier has a 72.52 percent accuracy value, whereas the DT has a 70.32 percent accuracy value. SVM appears to have a higher grade of heart failure prediction and accuracy than DT.

REFERENCES

[1] C. S. Dangare and S. S. Apte, "Improved study of heart disease prediction system using data mining classification techniques," *Int. J. Comput. Appl. Technol.*, vol. 47, no. 10, pp. 44–48, 2012.

[2] A. Shetty and C. Naik, "Different data mining approaches for predicting heart disease," *International Journal of Innovative in Science Engineering and Technology*, vol. 5, pp. 277–281, 2016.

[3] K. Thenmozhi and P. Deepika, "Heart disease prediction using classification with different decision tree techniques," *International Journal of Engineering Research and General Science*, vol. 2, no. 6, pp. 6–11, 2014.

[4] H. Rajaguru and S. K. Prabhakar, *KNN Classifier and K-Means Clustering for Robust Classification of Epilepsy from EEG Signals. A Detailed Analysis*. Anchor Academic Publishing, 2017.

[5] C. Sitawarin and D. Wagner, "Minimum-Norm Adversarial Examples on KNN and KNN based Models," *2020 IEEE Security and Privacy Workshops (SPW)*. 2020. doi: 10.1109/spw50608.2020.00023.

[6] G. G. N. Geweid and M. A. Abdallah, "A New Automatic Identification Method of Heart Failure Using Improved Support Vector Machine Based on Duality Optimization Technique," *IEEE Access*, vol. 7. pp. 149595–149611, 2019. doi: 10.1109/access.2019.2945527.

[7] L. Y. Zhou, F. P. Shan, K. Shimizu, T. Imoto, H. Lateh, and K. S. Peng, "A comparative study of slope failure prediction using logistic regression, support vector machine and least square support vector machine models." 2017. doi: 10.1063/1.4995939.

[8] J. Vepa, "Classification of heart murmurs using cepstral features and support vector machines," *2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. 2009. doi: 10.1109/iembs.2009.5334810.

[9] M. M. Azmy, "Classification of normal and abnormal heart sounds using new mother wavelet and support vector machines," *2015 4th International Conference on Electrical Engineering (ICEE)*. 2015. doi: 10.1109/intee.2015.7416684.

[10] Y. Xing, J. Wang, Z. Zhao, and A. Gao, "Combination Data Mining Methods with New Medical Data to Predicting Outcome of Coronary Heart Disease," in *2007 International Conference on Convergence Information Technology (ICCIT 2007)*, Nov. 2007, pp. 868–872.

[11] R. C. Deo, "Machine Learning in Medicine," *Circulation*, vol. 132, no. 20, pp. 1920–1930, Nov. 2015.

[12] S. Gheena and D. Ezhilarasan, "Syringic acid triggers reactive oxygen species-mediated cytotoxicity in HepG2 cells," *Hum. Exp. Toxicol.*, vol. 38, no. 6, pp. 694–702, Jun. 2019.

[13] P. Neelakantan, D. Grotra, and S. Sharma, "Retreatability of 2 mineral trioxide aggregate-based root canal sealers: a cone-beam computed tomography analysis," *J. Endod.*, vol. 39, no. 7, pp. 893–896, Jul. 2013.

[14] M. C. Putchala, P. Ramani, H. J. Sherlin, P. Premkumar, and A. Natesan, "Ascorbic acid and its pro-oxidant activity as a therapy for tumours of oral cavity -- a systematic review," *Arch. Oral Biol.*, vol. 58, no. 6, pp. 563–574, Jun. 2013.

[15] P. U. A. Wahab, M. Madhulaxmi, P. Senthilnathan, M. R. Muthusekhar, Y. Vohra, and R. P. Abhinav, "Scalpel Versus Diathermy in Wound Healing After Mucosal Incisions: A Split-Mouth Study," *J. Oral Maxillofac. Surg.*, vol. 76, no. 6, pp. 1160–1164, Jun. 2018.

[16] S. I. DeSouza, M. R. Rashmi, A. P. Vasanthi, S. M. Joseph, and R. Rodrigues, "Mobile phones: the next step towards healthcare delivery in rural India?," *PLoS One*, vol. 9, no. 8, p. e104895, Aug. 2014.

[17] D. Sajan, K. Udaya Lakshmi, Y. Erdogdu, and I. H. Joe, "Molecular structure and vibrational spectra of 2,6-bis(benzylidene)cyclohexanone: a density functional theoretical study," *Spectrochim. Acta A Mol. Biomol. Spectrosc.*, vol. 78, no. 1, pp. 113–121, Jan. 2011.

[18] A. K. Danda, "Comparison of a single noncompression miniplate versus 2 noncompression miniplates in the treatment of mandibular angle fractures: a prospective, randomized clinical trial," *J. Oral Maxillofac. Surg.*, vol. 68, no. 7, pp. 1565–1567, Jul. 2010.

[19] A. K. Danda, M. R. Muthusekhar, V. Narayanan, M. F. Baig, and A. Siddareddi, "Open versus closed treatment of unilateral subcondylar and condylar neck fractures: a prospective, randomized clinical study," *J. Oral Maxillofac. Surg.*, vol. 68, no. 6, pp. 1238–1241, Jun. 2010.

[20] R. Robert, C. Justin Raj, S. Krishnan, and S. Jerome Das, "Growth, theoretical and optical studies on potassium dihydrogen phosphate (KDP) single crystals by modified Sankaranarayanan–Ramasamy (mSR) method," *Physica B Condens. Matter*, vol. 405, no. 1, pp. 20–24, Jan. 2010.

[21] M. S. Kumar, G. Vamsi, R. Sripriya, and P. K. Sehgal, "Expression of matrix metalloproteinases (MMP-8 and -9) in chronic periodontitis patients with and without diabetes mellitus," *J. Periodontol.*, vol. 77, no. 11, pp. 1803–1808, Nov. 2006.

[22] A. S. Felicita, S. Chandrasekar, and K. K. Shanthasundari, "Determination of craniofacial relation among the subethnic Indian population: a modified approach - (Sagittal relation)," *Indian J. Dent. Res.*, vol. 23, no. 3, pp. 305–312, May 2012.

[23] R. A. Azeem and N. M. Sureshbabu, "Clinical performance of direct versus indirect composite restorations in posterior teeth: A systematic review," *J. Conserv. Dent.*, vol. 21, no. 1, pp. 2–9, Jan. 2018.

[24] V. S. Devi and B. K. Gnanavel, "Properties of concrete manufactured using steel slag," *Procedia Eng.*, vol. 97, pp. 95–104, 2014.

[25] P. Neelakantan, C. Subbarao, C. V. Subbarao, G. De-Deus, and M. Zehnder, "The impact of root dentine conditioning on sealing ability and push-out bond strength of an epoxy resin root canal sealer," *Int. Endod. J.*, vol. 44, no. 6, pp. 491–498, Jun. 2011.

[26] V. Krishnan and T. Lakshmi, "Bioglass: A novel biocompatible innovation," *J. Adv. Pharm. Technol. Res.*, vol. 4, no. 2, pp. 78–83, Apr. 2013.

[27] A. Mootha, S. Malaiappan, N. D. Jayakumar, S. S. Varghese, and J. Toby Thomas, "The Effect of Periodontitis on Expression of Interleukin-21: A Systematic Review," *Int. J. Inflam.*, vol. 2016, p. 3507503, Feb. 2016.

[28] T. Lakshmi, V. Krishnan, R. Rajendran, and N. Madhusudhanan, "Azadirachta indica: A herbal panacea in dentistry - An update," *Pharmacogn. Rev.*, vol. 9, no. 17, pp. 41–44, Jan. 2015.

[29] A. Mebazaa, "Acute Heart Failure Deserves a Log-Scale Boost in Research Support," *JACC: Heart Failure*, vol. 6, no. 1. pp. 76–79, 2018. doi: 10.1016/j.jchf.2017.09.012.

[30] D. A. L. Kafaf, D. AL Kafaf, D.-K. Kim, and L. Lu, "B-kNN to Improve the Efficiency of kNN," *Proceedings of the 6th International Conference on Data Science, Technology and Applications*. 2017. doi: 10.5220/0006393301260132.

[31] J. Marín-García, "Mechanical Circulatory Support and Heart Transplantation in Children with Severe Refractory Heart Failure," *Heart Failure*. pp. 297–312, 2010. doi: 10.1007/978-1-60761-147-9_15.

[32] D. Chandna, "Diagnosis of Heart Disease Using Data Mining Algorithm," 2014, Accessed: Jun. 24, 2021. [Online]. Available: https://www.semanticscholar.org/paper/ddc88ccea3d476bca2cf14ae6c4b3f51284cc5a6

[33] L. Nordgren and A. Söderlund, "Received and needed social support in relation to sociodemographic and socio-economic factors in a population of people on sick leave due to heart failure," *ESC Heart Failure*, vol. 4, no. 1. pp. 46–55, 2017. doi: 10.1002/ehf2.12121.

[34] Z. Obermeyer and E. J. Emanuel, "Predicting the Future - Big Data, Machine Learning, and Clinical Medicine," *N. Engl. J. Med.*, vol. 375, no. 13, pp. 1216–1219, Sep. 2016.

[35] D. Swain, P. K. Pattnaik, and P. K. Gupta, *Machine Learning and Information Processing: Proceedings of ICMLIP 2019*. Springer Nature, 2020.

[36] Á. Jobbágy, *5th European Conference of the International Federation for Medical and Biological Engineering 14 - 18 September 2011, Budapest, Hungary*. Springer Science & Business Media, 2012.

Bhatia, Sumit, Praveen Prakash, and G. N. Pillai. 2008. "SVM Based Decision Support System for Heart Disease Classification with Integer-Coded Genetic Algorithm to Select Critical Features." In Proceedings of the World Congress on Engineering and Computer Science, 34–38.