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Accurate and Predictable Cardiovascular Disease Detection by Machine Learning

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ABSTRACT
The first step in treating a disease is identifying and predicting it in patients. In the area of at-risk patient detection, we evaluate machine learning algorithms and identify important variables in the data that lead to this disease. To match with the other sectors, there is a large amount of data in the health sector that could be used to deal with various illnesses. One of the rising health concerns is cardiovascular disease that can be effectively treated if it is detected early on. The use of ML algorithms is essential for this purpose. The different algorithms for machine learning, as well as the various features that can be used to train these algorithms for cardiovascular detection, have all been discussed. In our survey questionnaire analysis, we have demonstrated that automated identification mechanisms for patients at risk of diabetes and cardiovascular diseases can be built using machine learning models. Additionally, we also identify key contributors to the prediction, which can be further investigated for their possible consequences on electronic health records.
Keywords: Cardiovascular, Cardiovascular Detection, Machine Learning (ML), Feature learning; Health analytics

INTRODUCTION
The health industry requires assistance to address a variety of concerns. A health-care system can assist this industry in improving its performance and assisting people in resolving health-related concerns. Cardiovascular disease is one of the most deadly diseases nowadays. This sickness is fairly common among people, and it can even affect children. This condition is extremely hazardous and can result in death. This disease is discovered through a person's blood test. If a person's blood sugar level is higher than usual, he is labeled a cardiovascular patient.
With the passage of time, the number of cardiovascular patients continues to rise. According to experts (Dinh et al., 2019; Kilic, 2020), the number of cardiovascular patients will rise by 55 percent by 2035, with one death due to cardiovascular disease occurring every six to ten seconds. Cardiovascular mellitus is a complex type of severe disease that can be caused by insulin resistance (Varma et al., 2014). The discovery of an anti-diabetic medicine is currently a major issue (Sakurai et al., 2002). There is a vast quantity of information available about this condition and its patients. This information must be used for the benefit of cardiovascular patients. Machine learning (ML) is increasingly being used in a variety of industries to solve problems. Researchers (Vadlamudi, 2019) employed machine learning algorithms to anticipate stock market prices. These algorithms can also be applied to the medical field. These algorithms, for example, were utilized by researchers (Finkelstein &CheolJeong, 2017) to predict asthma at an early stage. According to researchers (Paruchuri, 2018), the health-care industry collects a large amount of data about patients. This information must be utilized effectively. They used this data collection to detect cardiovascular disease.
The goal of this literature review is to emphasize the importance of cardiovascular disease early detection. Machine learning's usefulness in this area will also be highlighted. We'll go over the many characteristics and machine learning techniques that can be used to diagnose cardiovascular disease. The literature review is organized as follows: part two contains the methodology, section three contains the Research Questions, section four contains the search process, section five contains the results and discussion, and section six provides the conclusion.
For this literature study, we've devised two research questions. In the result and discussion section, these RQs will be discussed in depth.

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RQ 1: Why is machine learning necessary for early detection of cardiovascular disease and what are the various attributes that can be used to accomplish this?
RQ 2: What are the various machine learning algorithms that can be used for cardiovascular prediction or detection?
We conducted a search to compile the most pertinent papers on the subject. Our search procedure consisted of several steps. The first step was to eliminate papers with irrelevant titles. The second step was to eliminate papers with irrelevant abstracts. The remaining papers were thoroughly examined in the third step, and based on their complete content, we excluded those whose content was not relevant to our topic.
In different databases such as the IEEE, ACM, and other similar ones, there are a large number of papers that can be found. It is necessary to establish criteria for selecting papers that meet the requirements. The criteria that we used for including papers was based on the language of the paper and its complete availability; that is, only papers that were completely available and whose language was English were included, and the rest of the papers were excluded. In this study, the content of the papers was taken into consideration when determining the overall quality of the papers. When a paper has a strong content presentation, it is referred to as a good quality paper.

DATA MINING AND MODELING: DATASET PREPROCESSING

First, data mining methods and techniques are used to prepare raw patient records for training and testing machine learning models. Before preprocessing, raw patient data was extracted from the database. Any undecipherable values from the database were converted to null representations during the preprocessing stage.
The goal in developing a data-driven model was to extract all possible variables from the raw NHANES dataset. The data was checked for its continuity and accessibility across various categories and years. This was important, as NHANES has a large set of datasets with variable categorizations on an annual cycle. Missing data was found to be the result of conditioning question responses on previous questions (such as age, gender, or pregnancy status). In addition, inconsistent data collection by NHANES caused discontinuities in the data. Other names were used during various cycles. Based on the manual analysis, variable names were recoded. 189 of approximately 3900 variables from the NHANES database could be used continuously across all cycles of the NHANES database, from 1999 to 2014. The dataset was analyzed for missing values, and any that had more than 50% of the values missing were excluded. This caused a further reduction in variables to 123 for the 1999-2014 cycle.
It was decided to use the CVD dataset from 2007 to 2014 because this timeframe allowed for the greatest number of variables to be collected (131). The physical activity variables included in the dataset, which are considered important risk factors for cardiovascular disease, were specifically chosen for inclusion in the study (Powell et al., 1987). Each dataset was further subdivided into two categories: laboratory (which contains laboratory results) and no laboratory (which contains only survey data). Laboratory results were any feature variables in the dataset that were derived from blood or urine tests, regardless of how they were obtained. Because the data has been reclassified into these groups, it is possible to analyze the performance of machine learning models in cases where laboratory results are not available for patients, which allows for the identification of at-risk patients based solely on a survey questionnaire.
Figure 1 depicts the flow of information from raw data to the development of predictive models and the evaluation of those models in order to determine the likelihood that a subject will develop diabetes or cardiovascular disease. Three distinct stages of operation are involved in the pipeline's operation: 1) data mining and modeling, 2) model development, and 3) model evaluation.

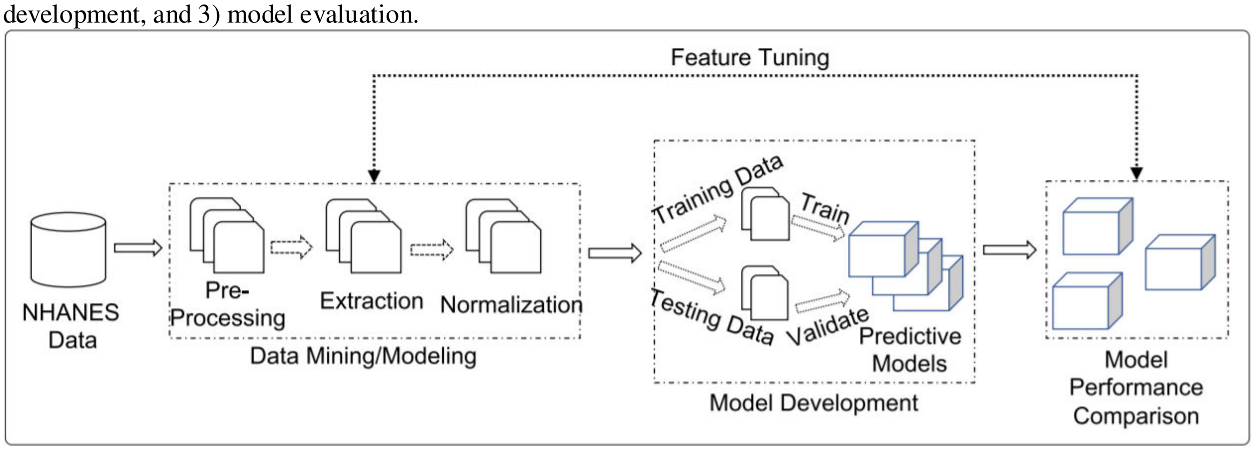

Figure 1: Pipeline for Model Development and Evaluation. A flow chart depicting the process of data processing and model development (Dinh et al., 2019)

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RESULT AND DISCUSSION

CVD prediction the detection of cardiovascular disease at-risk patients was approximately equal in all models, such as logistic regression, will give comparable results. The imbalanced data, with zero-labeled and one-labeled samples at 7,012 and 1,447 respectively, contributes to this being partly the result of a lack of a large number of observations in the data. Since there are many training examples, but only limited computational resources, simple models like Logistic Regression are preferable when applying ensemble models (WEM, RFC, and XGBoost). At 0.7% increase in expected results, models based on lab variables don't show any significant performance gain. A predictive model based on survey data only could be used to help determine if a patient has cardiovascular disease. The main features of non-laboratory data are age, diastolic and systolic blood pressure, self-reported greatest weight, chest pain, alcohol consumption, and family history of heart attacks. Alcohol, heart disease, and chest pain have all been associated with each other in previous studies (Nilsson et al., 2003; Britton & McKee, 2000; Friedlander et al., 1998). Lloyd-Jones et al. (2006) conducted a study that showed that patients' age is a critical risk factor that our models also identify. Many feature importance variables, such as demographics, diet, and physical characteristics, are common across diabetes and cardiovascular patients. The study conducted by Stamler et al. (1993) identified factors such as age stratum, ethnicity, and diabetes as critical contributors to cardiovascular disease. The laboratory-based data analysis suggests age, LDL and HDL cholesterol, chest pain, diastolic and systolic blood pressure, self-reported greatest weight, calorie intake, and family history of cardiovascular problems as important factors. Previous research shows that LDL and HDL cholesterol are risk factors for cardiovascular diseases (Shepherd et al., 2006; Gordon et al., 1989). Segmented neutrophils, monocyte, lymphocyte, and eosinophilic counts are important in this classification model. Similarly, results that are not measured in a laboratory have reappeared on the list of factors to focus on.

Cardiovascular disease is one of the most common diseases that affects people in different parts of the world. The World Health Organization (WHO) is also conducting research in order to determine the most effective treatment for this disease (Vadlamudi, 2018). With technological advancements, it is vital to leverage technology in the health industry to address the issue of cardiovascular disease. Obviously, this will not totally cure the problem, but early detection of cardiovascular disease will aid in the treatment of cardiovascular disease. Machine learning (ML) offers a variety of algorithms that may be used to make predictions. The main goal of machine learning is to make computers capable of learning from their past experiences and making predictions (Wilson &Keil, 2001; Kaur et al., 2017). Machine learning can be used in a variety of fields, including search engines, traffic management, gaming, email screening, and disease prediction, to name a few (Jordan & Mitchell, 2015; Sattigeri et al., 2014; Li &Arandjelovic, 2017). ML is now being used in the health sector for a variety of objectives. These include liver disease diagnostics, risk assessment, and cancer classification (Libbrecht& Noble, 2015; Kourou et al., 2015). The study employed the SVM machine learning method to diagnose liver disease (Hashem &Mabrouk, 2014).

The algorithms of machine learning are usually divided into three types (Paruchuri, 2019). There are three types of learning: supervised, unsupervised, and reinforced. A logistic model for the prediction of cardiovascular disease was created by researchers (Bagherzadeh-Khiabani et al., 2016). They looked for the most appropriate predictive features for this. The higher the accuracy, the more accurate the predictive features are. The random forest was employed by researchers (Robnik-ikonja&Kononenko, 2003) to determine the best cardiovascular prognostic features. Researchers utilize machine learning to classify cardiovascular diseases (Roychowdhury et al., 2013).

The development of any diagnosis software in the healthcare sector necessitates the software's ability to forecast outcomes. Cardiovascular disease is a condition that can affect a patient's entire body (Kaur et al., 2012). Researchers (Lloyd-Jones et al., 2006) employed machine learning algorithms to detect eye problems induced by cardiovascular illness. Predicting or detecting these diseases at an early stage is critical.

RQ 1: Why is machine learning necessary for early detection of cardiovascular disease and what are the various attributes that can be used to accomplish this?

There is an enormous amount of data available in almost every industry. Because this information is collected electronically, it is simple to apply machine learning algorithms for a variety of purposes. Manual record-keeping is nearly complete in each sector, with the exception of public utilities. Because the use of databases and computers makes it simple to manage and collect data, they are becoming increasingly popular. As a result, each industry generates a large amount of data, which can then be used to perform various tasks such as prediction and detection using machine learning. One of the most pressing issues in the health sector is the early detection of cardiovascular disease so that doctors can begin treating patients as soon as possible. The data set available in the hospitals can be used to train the machine learning algorithms used for this purpose. Researchers (Paruchuri, 2018) used machine learning algorithms to detect Predictable Cardiovascular Disease in its early stages. This is the most common type of cardiovascular disease, with this type of cardiovascular disease accounting for 90 percent of all cardiovascular disease patients. Various researchers have used machine learning to detect cardiovascular disease at an early stage in

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order to prevent the various issues that can arise as a result of cardiovascular disease (Paruchuri et al., 2021). It is essential to predict cardiovascular disease early on in order to begin treatment as soon as possible. It is necessary to check the medical records and health information of the individuals in order to accomplish this, which is extremely time consuming if done manually. The traditional methods of dealing with a large amount of data are ineffective in this situation (Ahmed et al., 2021; Paruchuri, 2021). As a result, it is necessary to employ the ML for this purpose. When it comes to training machine learning algorithms, selecting the most appropriate features can be difficult. Because it consumes less time and produces more accurate predictions, using the most accurate features for training can be advantageous in terms of both time and accuracy (Vadlamudi, 2021). There are several characteristics or characteristics that are used by scientists in the training and detection of cardiovascular diseases, which are listed below.

RQ 2: What are the various machine learning algorithms that can be used for cardiovascular prediction or detection?

Machine learning has made a variety of tasks in a variety of industries much more straightforward. The algorithms of machine learning (ML) can be used to deal with the problem of cardiovascular detection and prediction. When it comes to the classification of cardiovascular diseases, researchers (Dinh et al., 2019) used genetic programming. In the health sector, models that aid in the prediction or assessment of risk are very popular. For their research, researchers (Paruchuri, 2019) used machine learning approaches. ML has been used by a number of researchers to detect cardiovascular disease (Amin &Vadlamudi, 2021; Vadlamudi et al., 2021). The following are some of the most popular machine learning algorithms that are used for detecting cardiovascular diseases.

The steps that can be taken in order to obtain a prediction result from any of these machine learning algorithms are depicted in the diagram below.

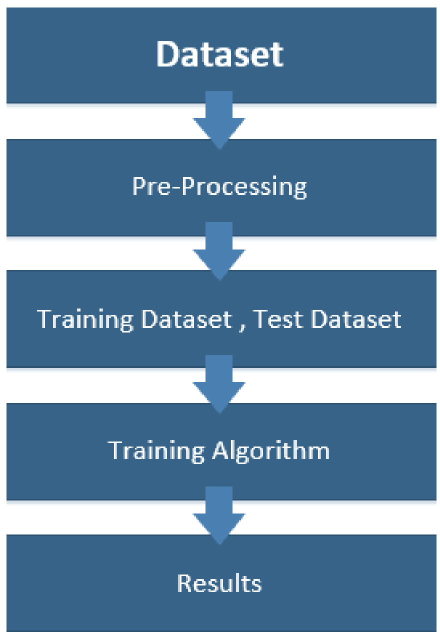

Figure 1: Algorithm Training

Logistic Regression: This algorithm was used by researchers (Dinh et al., 2019) to predict the cardiovascular system's performance. They made modifications to this algorithm in order to improve its accuracy. The previous accuracy rate was 79 percent, and they increased it to 90.4 percent as a result of their efforts.

Random Forest: The researchers (Britton & McKee, 2000) used random forest to identify the type of cardiovascular disease that was being investigated. Ganapathy and colleagues (Ganapathy et al., 2020) have also used this algorithm and compared it to other machine learning methods. Based on their findings, they declared that this algorithm was a superior algorithm for cardiovascular detection.

SVM: According to researchers (Dinh et al., 2019), the number of cardiovascular patients is increasing all the time. It is necessary to use an automated way for detecting the cardiovascular. In order to accomplish this, they used this algorithm. This algorithm was developed by researchers (Paruchuri, 2020) for the purpose of early detection of eye disease caused by cardiovascular disease.

This algorithm is used by the researchers (Azad et al., 2021) as a novel approach for predicting the cardiovascular system at an early stage of the disease. They created a web-based interface that displays the prediction based on various input values, such as age, insulin level, and so on.

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ANALYTIC REPORT

AI in the health care industry is projected to grow from $2.1 billion to $36.1 billion by 2025 (Kilic, 2020). In addition, the cardiovascular health care arena will also be affected. In this review, numerous potential applications of AI and ML to cardiovascular medicine and surgery are highlighted. Risk modeling has played a vital role in both the NCDR and STS as well as other similar cardiovascular data registries for decades. While there is much promise for ML in the cardiovascular realm, due to several criteria, there is a need to be cautiously optimistic. Accuracy is most important. In particular situations, people's tolerance for inaccurate information may vary. Tumors in the chest, such as tension pneumothorax, may present life-threatening dangers when seen on chest roentgenograms. In these scenarios, an algorithm with a higher false-positive rate is more appropriate than one with a lower false-negative rate. Missing a frequent event for the sake of higher accuracy will generally be more acceptable than dealing with a less frequent event.

Also, the reference standard by which the ML model is compared is crucial. On imaging interpretation, the public may be hesitant to trust ML centers if they believe these technologies are designed to fully replace the human aspect of interpretation. It is more likely than this: Radiologists and cardiologists use the technology to triage scans, supplementing rather than replacing them. Other examples where ML could supplement, rather than replace, existing methods include natural language processing—for example, where ML algorithms can alert a physician to the electronic medical record containing possible treatment avenues. Predictive analytics may include ML in which certain subsets of patients and events may be more accurately predicted by machine learning and other traditional approaches. Some ML algorithms have also been described as a “black box” where the details of the model are unknown. It raises the question of how physicians can modify certain risk factors in patients without knowing what is impacting their outcome. Some ML algorithms, such as XGBoost, display the relative importance of variables in predicting a particular outcome. It resembles a logistic regression model with regard to individual risk factors and their predictive importance.

There are ethical issues that would need to be addressed before ML can be widely implemented in clinical practice. Privacy is an ethical issue. Human immunodeficiency virus (HIV) status, intravenous drug use, and smoking history can all potentially be inferred by ML algorithms when a patient does not reveal these personal health details. These factors could potentially impact treatment recommendations against specific patient populations based on machine learning. If a black box ML algorithm sheds very little insight into its individual predictive factors, then this algorithm could systematically bias recommendations for certain patient groups. The value of ML models, in clinical practice, requires continual evaluation. For instance, to make sure that the ML algorithm's mistakes don't harm patients, safety monitoring could be utilized. Standard of care can be compared to ML-supported care in a clinical trial format where an ML algorithm is implemented.

CONCLUSION

To summarize, the application of machine learning to health care is currently in an exciting stage. This is a bit of a "blank canvas," and the specifics of how this technology will be used and implemented in clinical practice will have to be determined in the future. Previous studies have found that a variety of machine learning techniques can be used to interpret medical imaging in an automated manner, to process electronic medical records, and provide predictive models. Despite the fact that science is progressing at an exponential rate, translating that science into actual practice will necessitate careful deliberation among a wide range of stakeholders. Overall, the goal will be to employ this technology in order to provide more informed and effective care while also doing so in a more efficient and cost-effective manner.

Cardiovascular disease is on the rise in both developed and developing countries, and it is expected to continue to rise. The development of an effective solution to deal with this disease is urgently required. The healthcare sector can use machine learning to detect this disease early on, allowing doctors to assist the patient in recovering from the disease. This disease can also be the cause of a variety of other diseases, which can also be detected using ML. In order to deal with the growing epidemic of the disease in the modern era, it is necessary to employ modern tools.

It also investigates the utility of such models in detecting patients with cardiovascular disease in survey datasets, which is the focus of this paper. As demonstrated in our analysis, machine-learned models are capable of detecting the aforementioned diseases in patients with high accuracy. It is possible that such a model will find real-world application in the form of a web-based tool, in which a survey questionnaire will be used to assess the disease risk of participants. Depending on their results, the participants can choose to have a more thorough physical examination with a doctor. As part of our future efforts, we intend to investigate the effectiveness of variables found in electronic health records in order to develop more accurate models.

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REFERENCES

Ahmed, A. A. A.; Paruchuri, H.; Vadlamudi, S.; &Ganapathy, A. (2021). Cryptography in Financial Markets: Potential Channels for Future Financial Stability. Academy of Accounting and Financial Studies Journal, 25(4), 1–9. https://doi.org/10.5281/zenodo.4774829

Alaa AM, Bolton T, Di Angelantonio E, Rudd JHF, van der Schaar M. Cardiovascular disease risk prediction using automated machine learning: A prospective study of 423,604 UK Biobank participants. PLoS One. 2019 May 15;14(5):e0213653. doi: 10.1371/journal.pone.0213653. PMID: 31091238; PMCID: PMC6519796.

Amin, R., &Vadlamudi, S. (2021). Opportunities and Challenges of Data Migration in Cloud. *Engineering International*, *9*(1), 41-50. https://doi.org/10.18034/ei.v9i1.529

Azad, M. M., Ganapathy, A., Vadlamudi, S., Paruchuri, H. (2021). Medical Diagnosis using Deep Learning Techniques: A Research Survey.*Annals of the Romanian Society for Cell Biology*, *25*(6), 5591–5600. Retrieved from https://www.annalsofrscb.ro/index.php/journal/article/view/6577

Bagherzadeh-Khiabani, F., Ramezankhani, A., Azizi, F., Hadaegh, F., Steyerberg, E. W., &Khalili, D. J. J. o. c. e. (2016). A tutorial on variable selection for clinical prediction models: feature selection methods in data mining could improve the results. *71*, 76-85.

Britton A, McKee M. The relation between alcohol and cardiovascular disease in eastern europe: explaining the paradox. J Epidemiol Community Health. 2000;54(5):328–32.

Dinh A, Miertschin S, Young A, Mohanty SD. A data-driven approach to predicting diabetes and cardiovascular disease with machine learning. BMC Med Inform DecisMak. 2019 Nov 6;19(1):211. doi: 10.1186/s12911-019-0918-5. PMID: 31694707; PMCID: PMC6836338.

Finkelstein, J., &CheolJeong, I. J. A. o. t. N. Y. A. o. S. (2017). Machine learning approaches to personalize early prediction of asthma exacerbations. *1387*(1), 153.

Friedlander Y, Siscovick DS, Weinmann S, Austin MA, Psaty BM, Lemaitre RN, Arbogast P, Raghunathan T, Cobb LA. Family history as a risk factor for primary cardiac arrest. Circulation. 1998;97(2):155–160.

Ganapathy, A., Redwanuzzaman, M., Rahaman, M. M., & Khan, W. (2020). Artificial Intelligence Driven Crypto Currencies. *Global Disclosure of Economics and Business*, *9*(2), 107-118. https://doi.org/10.18034/gdeb.v9i2.557

Gordon DJ, Probstfield JL, Garrison RJ, Neaton JD, Castelli WP, Knoke JD, Jacobs Jr DR, Bangdiwala S, Tyroler HA. High-density lipoprotein cholesterol and cardiovascular disease. four prospective american studies. Circulation. 1989;79(1):8–15.

Hashem, E. M., &Mabrouk, M. S. J. A. J. o. I. S. (2014). A study of support vector machine algorithm for liver disease diagnosis. *4*(1), 9-14.

Jordan, M. I., & Mitchell, T. M. J. S. (2015). Machine learning: Trends, perspectives, and prospects. *349*(6245), 255-260.

Kaur, H., Chauhan, R., & Ahmed, Z. J. B. H. S. R. (2012). Role of data mining in establishing strategic policies for the efficient management of healthcare system–a case study from Washington DC area using retrospective discharge data. *12*(1), 1-2.

Kaur, H., Lechman, E., &Marszk, A. J. T. D. W. E. (2017). Catalyzing development through ICT adoption. *4*.

Kilic A. Artificial Intelligence and Machine Learning in Cardiovascular Health Care. Ann Thorac Surg. 2020 May;109(5):1323-1329. doi: 10.1016/j.athoracsur.2019.09.042. Epub 2019 Nov 7. PMID: 31706869.

Kourou, K., Exarchos, T. P., Exarchos, K. P., Karamouzis, M. V., Fotiadis, D. I. J. C., & journal, s. b. (2015). Machine learning applications in cancer prognosis and prediction. *13*, 8-17.

Li, J., &Arandjelovic, O. (2017). *Glycaemic index prediction: a pilot study of data linkage challenges and the application of machine learning*. Paper presented at the 2017 IEEE EMBS International Conference on Biomedical & Health Informatics (BHI).

Libbrecht, M. W., & Noble, W. S. J. N. R. G. (2015). Machine learning applications in genetics and genomics. *16*(6), 321-332.

Lloyd-Jones DM, Leip EP, Larson MG, d'Agostino RB, Beiser A, Wilson PW, Wolf PA, Levy D. Prediction of lifetime risk for cardiovascular disease by risk factor burden at 50 years of age. Circulation. 2006;113(6):791–8.

Nilsson S, Scheike M, Engblom D, Karlsson L-G, Mölstad S, Akerlind I, Ortoft K, Nylander E. Chest pain and ischaemic heart disease in primary care. Br J Gen Pract. 2003;53(490):378–82.

Paruchuri, H. (2018). AI Health Check Monitoring and Managing Content Up and Data in CMS World. *Malaysian Journal of Medical and Biological Research*, *5*(2), 141-146. https://doi.org/10.18034/mjmbr.v5i2.554

ISSN: 0975-3583, 0976-2833 VOL 12, ISSUE 03, 2021

Paruchuri, H. (2019). Market Segmentation, Targeting, and Positioning Using Machine Learning. *Asian Journal of Applied Science and Engineering*, *8*(1), 7-14. Retrieved from https://journals.abc.us.org/index.php/ajase/article/view/1193

Paruchuri, H. (2020). The Impact of Machine Learning on the Future of Insurance Industry. *American Journal of Trade and Policy*, *7*(3), 85-90. https://doi.org/10.18034/ajtp.v7i3.537

Paruchuri, H. (2021). Conceptualization of Machine Learning in Economic Forecasting. *Asian Business Review*, *11*(1), 51-58. https://doi.org/10.18034/abr.v11i1.532

Paruchuri, H.; Vadlamudi, S.; Ahmed, A. A. A.; Eid, W.; Donepudi, P. K. (2021). Product Reviews Sentiment Analysis using Machine Learning: A Systematic Literature Review. *Turkish Journal of Physiotherapy and Rehabilitation, 23*(2), 2362-2368, https://turkjphysiotherrehabil.org/pub/pdf/322/32-2-316.pdf

Powell KE, Thompson PD, Caspersen CJ, Kendrick JS. Physical activity and the incidence of coronary heart disease. Annu Rev Public Health. 1987;8(1):253–87

Robnik-Šikonja, M., &Kononenko, I. J. M. l. (2003). Theoretical and empirical analysis of ReliefF and RReliefF. *53*(1), 23-69.

Roychowdhury, S., Koozekanani, D. D., Parhi, K. K. J. I. j. o. b., & informatics, h. (2013). DREAM: diabetic retinopathy analysis using machine learning. *18*(5), 1717-1728.

Sakurai, H., Kojima, Y., Yoshikawa, Y., Kawabe, K., &Yasui, H. J. C. C. R. (2002). Antidiabetic vanadium (IV) and zinc (II) complexes. *226*(1-2), 187-198.

Sattigeri, P., Thiagarajan, J. J., Shah, M., Ramamurthy, K. N., &Spanias, A. (2014). *A scalable feature learning and tag prediction framework for natural environment sounds.* Paper presented at the 2014 48th Asilomar Conference on Signals, Systems and Computers.

Shepherd J, Barter P, Carmena R, Deedwania P, Fruchart J-C, Haffner S, Hsia J, Breazna A, LaRosa J, Grundy S, et al. Effect of lowering ldl cholesterol substantially below currently recommended levels in patients with coronary heart disease and diabetes: the treating to new targets (tnt) study. Diabetes Care. 2006;29(6):1220–6.

Stamler J, Vaccaro O, Neaton JD, Wentworth D, Group MRFITR, et al. Diabetes, other risk factors, and 12-yr cardiovascular mortality for men screened in the multiple risk factor intervention trial. Diabetes Care. 1993;16(2):434–444.

Vadlamudi, S. (2018). Agri-Food System and Artificial Intelligence: Reconsidering Imperishability. *Asian Journal of Applied Science and Engineering*, *7*(1), 33-42. Retrieved from https://journals.abc.us.org/index.php/ajase/article/view/1192

Vadlamudi, S. (2019). How Artificial Intelligence Improves Agricultural Productivity and Sustainability: A Global Thematic Analysis. *Asia Pacific Journal of Energy and Environment*, *6*(2), 91-100. https://doi.org/10.18034/apjee.v6i2.542

Vadlamudi, S. (2021). The Internet of Things (IoT) and Social Interaction: Influence of Source Attribution and Human Specialization. *Engineering International*, *9*(1), 17-28. https://doi.org/10.18034/ei.v9i1.526

Vadlamudi, S.; Paruchuri, H.; Ahmed, A. A. A.; Hossain, M. S.; &Donepudi, P. K. (2021). Rethinking Food Sufficiency with Smart Agriculture using Internet of Things. Turkish Journal of Computer and Mathematics Education, 12(9), 2541–2551. https://turcomat.org/index.php/turkbilmat/article/view/3738

Varma, K. V., Rao, A. A., Lakshmi, T. S. M., Rao, P. N. J. C., & Engineering, E. (2014). A computational intelligence approach for a better diagnosis of diabetic patients. *40*(5), 1758-1765.

Wilson, R. A., &Keil, F. C. (2001). *The MIT encyclopedia of the cognitive sciences*: MIT press.

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