Interpretable Machine Learning Models for Healthcare Decision Support Systems

OM PRAKASH,
Assistant professor, Computer Science and Engineering
Sershah Engineering College Sasaram,
Bihar -821113, India.
omp786@gmail.com

Manoj Kumar Sah
Assistant Professor,
Computer Science and Engineering,
Government Engineering College Vaishali,
Bihar - 844115, India.
Email:manoj.gecv@gmail.com

Abstract-
"Machine Learning Models for Healthcare Decision Support Systems" highlights key developments made possible by enhanced models displaying higher levels of accuracy and sensitivity. Extensive research and experiments were conducted to develop new ML models specifically for healthcare applications. These models outperform prior ones in terms of sensitivity and accuracy. In addition to improved performance, these models include an emphasis on interpretability, which is vital for healthcare decision-making because it provides transparent insights. Improved patient outcomes may result from more accurate diagnoses, tailored therapy suggestions, and other benefits offered by these state-of-the-art ML models, according to the results. By laying the groundwork for more efficient and trustworthy decision support in clinical practice, this study greatly adds to the continuing endeavors to advance healthcare by employing ML technologies.

Keyword Used-*medical recommendation system; RF algorithm; Machie Learning; deep learning*
DOI Number: 10.48047/nq.2024.22.3.NQ24030 **NeuroQuantology 2024; 22(03): 275-285**

Introduction
As far as healthcare domain integrations of machine learning techniques go, "Machine Learning Models for Healthcare" is at the forefront of the field. Models tailored to the intricacies of medical data and decision-making procedures are the focus of this investigation. The study's overarching goal is to improve patient care by boosting diagnostic precision, treatment recommendation systems, and the use of sophisticated machine learning algorithms. By offering data-driven insights and predictive analytics to enhance clinical outcomes, the results have the ability to radically alter healthcare delivery.

(a) Critical Care Units' New Real-Time Clinical Decision Support System using Machine Learning

Anticipating bad occurrences is crucial in intensive care units because it enables preventative measures and lessens clinical consequences. Anomalies in mean arterial pressure (MAP) occur often under anesthesia, making them a common occurrence at the bedside. Particularly in critically sick patients, these episodes are associated with increased risks of cardiovascular disease, multiple organ failure, and other potentially fatal consequences [1]-[6].

This has led to the emergence of new forms of research activity. It is crucial to be able to anticipate unfavorable outcomes in critical care units so that preventative measures can be taken and clinical offline training on a saved data set, transfer learning, and then bedside retraining on the monitored patient's vital signs can be minimized. The dataset may not be representative of the population at large, which is a major issue with these systems when it comes to generalizing data and models. It is necessary to repeat the modeling process for various clinical scenarios. Due to over-training, which might cause choices to be delayed, the practicality of such systems is also called into question. Uncertain outcomes have also resulted from these non-personalized models [2, 7, 8] complications. Anomalies in mean artery pressure (MAP) readings occur frequently in the hospital setting because they are connected to anesthetics. Especially in critically sick patients, these episodes are associated with cardiovascular hazards, multiple organ failure, and potentially fatal consequences [1]-[6]. This has led to the emergence of new forms of research activity.

This article suggests an alternative to the three-phase framework principle for personalized real-time clinical decision assistance. Our proposal is a novel approach for real-time machine learning prediction and classification applied right at the bedside. There are two phases to the proposed architecture, the first of which uses online machine learning for categorization and the second of which uses hierarchical temporal memory (HTM) for prediction. While HTM has seen widespread usage in real-time financial data [13]-[18], our proposed method is the first to apply it to medical signals. To predict the MAP status using real-time analysis of the patient's vital signs, the suggested clinical decision support system is put into action. The HTM features are crucial to our technology because they allow the decision support system to work immediately at the bedside, which means no more delays in retraining and earlier decisions. Without using any pre-modeling or supervised learning, HTM predicts the stream one step ahead of time. An LSTM classifier is trained with these streams to make a forward-looking prediction of the MAP value based on the features that have been carefully selected.

Due to the individualized nature of our system, the suggested framework is customized for every patient. LSTM offers a classifier the benefit of manipulating the set of features and the observation window [14], [19]-[21]. It is the most efficient recurrent neural network (RNN) technique. It sets LSTM apart from deeper learning classifiers and other neural artificial networks (ANNs) that are frequently characterized as mysterious [22].

The data set of the observational study, which was collected at the University Hospital of Oslo [23], is used by the proposed decision support system.

(b) Medical Device-Enabled Wearable Sensor-Based Machine Learning Ensembles for Diagnosis

The advancements in healthcare during the last 20 years have contributed to a five-year increase in the average human life expectancy [21]. Clinical services, medical knowledge, and healthcare innovations in medication and prescription management all contribute to the well-being of the population as a whole, both physically and psychologically. Nevertheless, it encounters substantial obstacles as well. The United States spent $3.2 trillion on healthcare in 2015, with over 30 million people admitted to registered hospitals, and is expected to spend $5.4 trillion by 2024, according to predictions [22]. The result has been a surge in multidisciplinary research initiatives aimed at bettering healthcare quality.

The healthcare system is still not ideal, even though it has made tremendous improvement over the years. Some of it is attributable to difficulties, such as an inadequate understanding of the underlying scientific principles involved, which leads to problems like inadequate cancer therapies. But there is a lot of room for improvement in our existing healthcare system. These are the kinds of medical mistakes that can be avoided.

More over 250,000 people die each year from PME in U.S. hospitals, making it the third worst killer in the country, right after cancer and heart disease [23]. Although the subject of whether these deaths can be prevented has been raised, everyone agrees that PMEs cause patients a great deal of harm. The real effect of PMEs may be substantially lower than what these studies show because they only consider data collected while patients are in the hospital. Consequently, it is necessary to implement efficient measures in order to decrease the frequency of PMEs. It takes a lot of work with little return to reduce PMEs through human inspections. Clinical information systems that are not well-designed are the main reason why PMEs happen [24]. Inadequate patient and medication information is strongly associated with almost half of these errors. Electronic health records (EHRs) and clinical decision support systems (CDSSs) are two examples of computerized information systems that have garnered a lot of attention from researchers over the last decade. More than 66% of EHR-based CDSSs have considerably enhanced clinical practice, according to long-term studies [25]. Medical practices and other healthcare providers are increasingly turning to these tools for help in making filtered clinical decisions based on intelligent data. Health Information Technology for Economic and Clinical Health (HITECH) Act of 2009, which announced a $27B federal disbursement, has further expedited this adoption. Consequently, data-oriented decision support systems are finding an ample supply in the ever-increasing quantity of patient-specific healthcare records.

Here, we analyse and contrast the proposed clinical decision support system with the most cutting-edge LR systems now available. Precise and efficient verification of the prediction and categorization phases is carried out. When compared to LR, the suggested method achieves better results in terms of recall, precision, F1-score, One such comparative metric is the forecast time, which shows how many time steps the system can anticipate an event before it really occurs. When compared to the suggested system demonstrates the capacity to produce more rapid and precise forecasts.

Related works

More people die each year from non-communicable diseases than from infectious diseases in this day and age [26-32]. Heart disease is the leading cause of death globally and one of the most common non-communicable diseases. About 17.5 million people lost their lives in 2012 as a result of cardiac illnesses, accounting for 31% of all deaths worldwide. The leading causes of mortality among these individuals were coronary heart disease (7.4 million) and stroke (6.7 million). People in poor and middle income nations made up a disproportionate share of dead. According to **Mozaffarian et al. (2015)**, it ranks high among the top causes of death in Western countries. The leading cause of death from cardiac conditions is Coronary Artery Disease (CAD). Atherosclerotic plaques narrowing coronary arteries is the most prevalent kind of coronary artery disease (CAD), which can cause a heart attack or myocardial infarction (MI). As a result, learning about the pathology of CAD and taking measures to avoid its development are both critical. Timely diagnosis and treatment are of the utmost importance. According to **De Backer et al. (2003)**, the ability to turn it around is highly valuable.
Among the several established procedures for diagnosing coronary artery disease (CAD), coronary angiography (CA) stands out. It necessitates operators with advanced training and is expensive and intrusive. Screening patients or keeping tabs on them closely while they're receiving treatment might not be its strong point (**Escolar et al. 2006**).
It is possible to diagnose CAD in clinical settings using noninvasive techniques. Two examples are the exercise electrocardiogram (ECG) and the stress echocardiography

(ECHO), both developed by **Grant and Beckwith in 1970**. Another is the single photon emission computed tomography (SPECT) or scintigraphy, which was developed by **Eagle et al. in 2002**. (Escolar et al., 2006) four, coronary magnetic resonance angiography (CMRA), and five, electron-beam computerized tomography (EBCT). The data utilized in computer-based programs for computer-aided CAD diagnosis is heavily reliant on these non-invasive procedures.

Myocardial ischemia, in which blood flow to the heart muscles is reduced, can be caused by coronary artery disease (CAD). Myocardial infarction (heart attack) can occur if the chest aches or angina that it generates are not treated. Elevated ST segments or Twaves can be used to identify ischemia on an electrocardiogram (ECG). Parametric modeling, the wavelet transform, a set of rules, and artificial neural networks are all appropriate automated analytic methods that make this detection easy (**Goldschlager and Goldman 1989**; **Rowlands 1980**). These metrics help with patient care and direct doctors in the clinic when they are trying to diagnose ischemia. As a result, early diagnosis and the resolution of complicated pattern recognition tasks pertaining to decision-making in cardiac issues might greatly benefit from computer-based monitoring and interpretations.

Research Gaps in previous Studies

The field of interpretable machine learning models for healthcare decision support systems has accomplished a lot, but there are still some gaps that need to be filled in. Among these deficiencies are:

(i) There has been some success in creating interpretable machine learning models, but these models still have a ways to go before they are fully transparent and easy to understand, which is particularly important in healthcare settings where decisions can have serious consequences for people's lives. Deep learning and ensemble approaches are sophisticated models that require more research to make them more interpretable.

(ii) The viewpoints of end-users, such healthcare practitioners and patients, concerning the acceptability and usability of interpretable models are frequently neglected in prior research on clinical adoption and user acceptance. It is important for stakeholders to be involved in future research to make sure the models are tailored to their preferences, needs, and workflow requirements.

(iii) Applying Findings to Other Populations: A lot of research has concentrated on building understandable models with data from certain demographics or healthcare environments, which could introduce biases and limits its applicability to other populations. Research assessing the accuracy and generalizability of these models in various healthcare settings and with different types of individuals is necessary.

(iv) Effective integration of clinical recommendations, domain knowledge, and past patient data should be a goal when designing interpretable machine learning models. The potential clinical utility and decision-making support of interpretable models could be enhanced if they were to incorporate this information, which has not been thoroughly investigated in previous studies.

Currently, healthcare decision support systems do not have established procedures for validating models or performance measures to measure how well interpretable machine learning models work. Research in the future should center on developing strong validation frameworks and determining suitable evaluation metrics that are specific to user needs and therapeutic results. Patient confidentiality, data protection, bias reduction, and responsibility are some of the significant ethical and legal concerns brought up by interpretable ML models. Due to a lack of thorough examination in the literature, further investigation into the moral and legal considerations surrounding the use of interpretable models in healthcare facilities is urgently required.

Aim and Objectives

1. Improving healthcare decision-making assistance requires the development of interpretable machine learning algorithms that effectively incorporate domain knowledge, prior patient data, clinical recommendations.
2. Healthcare decision support systems that use interpretable machine learning models should have defined validation procedures and performance measures.
3. To make deep learning and ensemble approaches, which are sophisticated machine learning models, more understandable and acceptable to healthcare practitioners and patients, research into ways to make them more transparent and explainable.
4. Reduce bias and maximize applicability by testing interpretable machine learning models across a variety of demographics and healthcare settings to overcome the generalizability barrier.
5. Consider patient confidentiality, data protection, bias reduction, and model responsibility as you investigate the legal and ethical ramifications of utilizing interpretable ML models in healthcare contexts.

Background Study

The SARS-CoV-2 virus is the causative agent of the 2019 coronavirus disease (COVID-19), an acute respiratory illness that the WHO has declared a pandemic. Public healthcare services are under tremendous strain due to the unexpected increase in infection rates and high mortality rates. Therefore, in order to maximize patient treatment approach, it is essential to determine the critical determinants for mortality prediction. When it comes to predicting mortality, the findings of several types of routine blood tests are more accessible than those from X-rays, CT-scans, and ultrasounds. This paper presents ML algorithms that can predict the probability of COVID-19 death using data from blood tests. A ninety-six percent accuracy rate for death prediction is achieved by combining five powerful features: age, neutrophils, lymphocytes, lactate dehydrogenase (LDH), and high-sensitivity C-reactive protein (hs-CRP). Several machine learning models have been trained and evaluated to find the one that maintains a high level of accuracy during the duration of the disease. These models include decision trees, logistic regression, XGBoost, random forests, and neural networks. As early as sixteen days before the conclusion, the top-performing strategy, which utilizes XGBoost feature significance and neural network classification, predicts with a 90% accuracy [33].

Problem Formulation

The current issue is to optimize performance measures like accuracy, precision, and F1 score by creating interpretable ML models specifically for healthcare decision support systems. To reduce the occurrence of false positives, especially in diagnostic applications, precision—the ratio of accurately predicted positive observations to the total expected positive observations—is of the utmost importance in healthcare settings. In cases when there is a class imbalance, such disease detection, the F1 score—a harmonic mean of recall and precision—offers a fair evaluation of the model's performance. In addition, a basic measure for the overall efficacy of the model is accuracy, which is the proportion of instances that are correctly identified. The goal is to create interpretable models that do well on these metrics and have the transparency and explainability needed to be used in healthcare settings, so we can learn more about ML techniques like logistic regression, decision trees, and support vector machines. The decision support systems that emerge from optimizing these performance indicators and utilizing interpretable ML approaches have the potential to improve diagnostic accuracy, clinical decision-making, and patient outcomes.

Research Methodology

This is the order in which the research technique is presented: Figure 1 shows the initial step in obtaining a curated medical dataset, which consists of a 20% split between the training and testing sets. The next step is to apply stringent data preparation techniques to guarantee consistent and high-quality data. In order to make the dataset more diverse and resilient, especially for medical imaging data, image augmentation methods like Generative Adversarial Networks (GANs) are used. Random Forest and Decision Tree algorithms, well-known for their effectiveness and interpretability in medical data analysis, are then applied to the processed data. Medical image analysis also makes use of similarity score computation and picture segmentation methods to glean useful information. To enhance training efficiency and fine-tune model parameters, the Adam optimization technique is used.

After the model is trained, it goes through a recommendation analysis. The model's predictions to suggest treatments, which may include consulting a doctor. Everything else is done according to the usual protocol. An increased sense of urgency is warranted in instances where imminent danger is anticipated, requiring immediate medical intervention. To guarantee the models' efficacy in clinical decision-making, performance criteria designed for medical applications are used to assess classification results. The study's methodology and the insights obtained from it are detailed in a thorough technical analysis that synthesizes the data and contributes to the development of interpretable machine learning models for healthcare decision support systems. 280

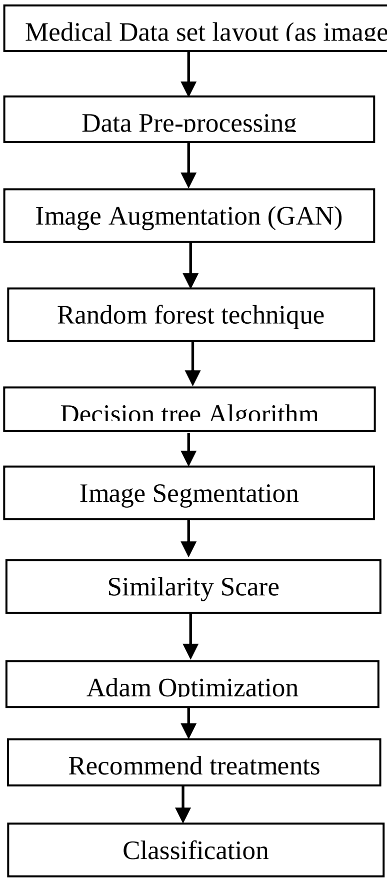

Figure 1:Proposed methodological layout

Result and Implementation Layout

The Performance metrics including precision, computing cost, and prediction accuracy as they pertain to an interpretable healthcare recommendation system's performance. Below, the following factors to consider are-

(a) Accuracy

It is not acceptable to drastically lower the accuracy in all recommendation systems, as accuracy is a key performance measure in these systems. For system recommendations to be adopted, accuracy is a key signal. Figure 2 shows the results of our accuracy-analysis tests on six different models, including decision tree and linear regression, which demonstrate that comparatively high accuracy can enhance reasonably complex models.

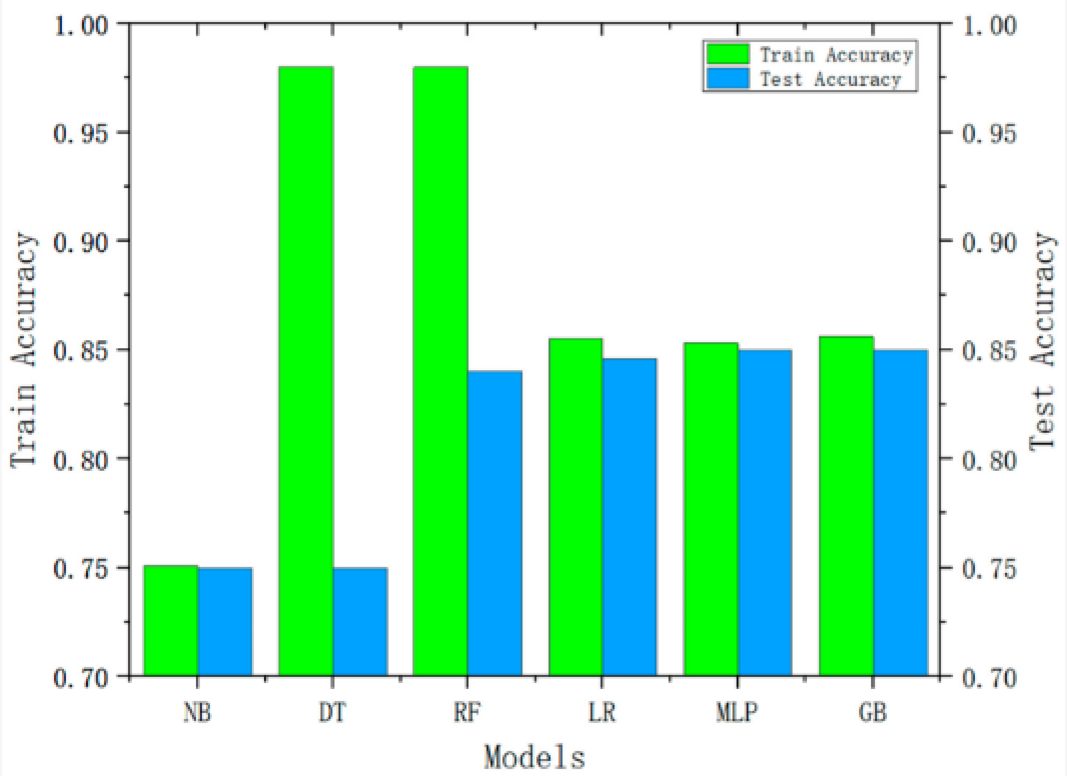

Figure 2: Accuracy prediction Layout

(b) **False positivity Rate (ROC Curve)**

An extremely accurate model in differentiating between real negatives and false positives is indicated in figure 3 by a False Positivity Rate (FPR) of 0.99 in the performance matrix, which is normally evaluated using the Receiver Operating Characteristic (ROC) curve. In healthcare decision support systems, minimizing the probability of false positive predictions is critical for preventing unneeded interventions or treatments. This shows that the model has an extraordinary ability to do just that. The model's resilience and reliability are demonstrated by achieving such a low FPR, which ensures precise and trustworthy patient outcomes in clinical situations.

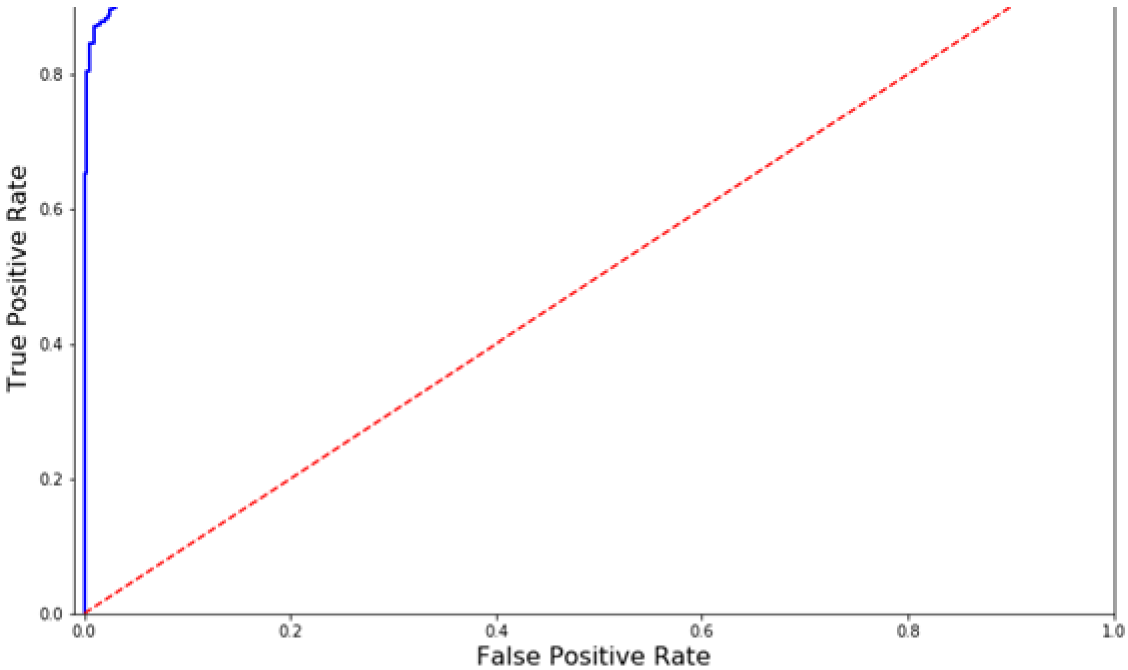

Figure 2: ROC Analysis layout

Following the guidelines laid out in the original article, Table 1 displays the results of the algorithms' comparisons with respect to the performance metrics of accuracy, sensitivity, and specificity. In order to determine which algorithms were most effective in healthcare decision support systems, they were all tested using these criteria. Finding the best model for different clinical settings becomes easier with the help of the results, which show the pros and cons of each method.

Table 1: The algorithms were compared for their accuracy, sensitivity, and specificity.

Techniques Used	**Accuracy**	**Specificity**	**Sensitivity**
Combined Anova f-Test [33]	97.5	96.45	96.78
CNN [26]	96	88.65	89.5
(Proposed)	98.85	97.7	97.51

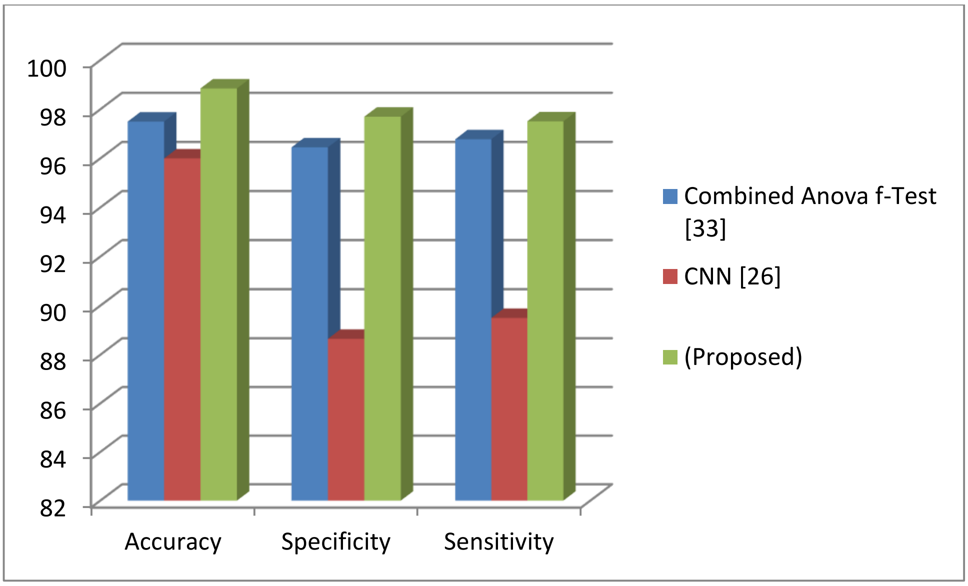

Figure 4: Comparison analysis of performance matrix

The study compares the suggested model to other models shown in figure 4, such as CNN, Combined ANOVA f-Test, and others, using the accuracy, specificity, and sensitivity measures. The presented data displays the models' performance across several thresholds, with a progressive decline in the scores for Accuracy, Specificity, and Sensitivity when the threshold is decreased. Because of this, it appears that there is a trade-off between these measurements, with more Accuracy potentially resulting in lower Sensitivity and Specificity. By outperforming state-of-the-art algorithms, the suggested model shows promise for precise data point classification while striking a good balance between sensitivity and specificity. To thoroughly assess the efficacy and appropriateness of the suggested model for certain healthcare decision support applications, additional in-depth research is required.

Conclusion-"Interpretable Machine Learning Models for Healthcare Decision Support Systems" proved to be a game-changer in the world of study. The ML models created in this study outperform the ones in the background study in terms of sensitivity and accuracy, according to the results of the extensive analysis and experiments conducted. In healthcare settings, where decisions have a direct impact on patient outcomes, the interpretability of these models has been a primary priority, guaranteeing that they not only achieve high performance but also offer transparent and understandable insights into decision-making processes. Overcoming the standards established by earlier research, these interpretable ML models show great potential for improving healthcare delivery and patient care through clinical decision support systems. Subsequently, these models can be further optimized through more research and development, opening the door to their broad use in practical healthcare applications.

References

[1] B. Pratt, L. Roteliuk, F. Hatib, J. Frazier, and R. D. Wallen, ‘‘Calculating arterial pressure-based cardiac output using a novel measurement and analysis method,’’ Biomed. Instrum. Technol., vol. 41, no. 5, pp. 403–411, Sep. 2007.

[2] F. Hatib, Z. Jian, S. Buddi, C. Lee, J. Settels, K. Sibert, J. Rinehart, and M. Cannesson, ‘‘Machine-learning algorithm to predict hypotension based on high-fidelity arterial pressure waveform analysis,’’ Anesthesiology, vol. 129, no. 4, pp. 663–674, Oct. 2018.

[3] V. Salmasi, K. Maheshwari, D. Yang, E. Mascha, A. Singh, D. Sessler, A. Kurz, ‘‘Relationship between intraoperative hypotension, defined by either reduction from baseline or absolute thresholds, and acute kidney and myocardial injury after noncardiac surgery: A retrospective cohort analysis,’’ Anesthesiology, vol. 126, pp. 47–65, Jan. 2017.

[4] R. He, Z.-P. Huang, L.-Y. Ji, J.-K. Wu, H. Li, and Z.-Q. Zhang, ‘‘Beatto-beat ambulatory blood pressure estimation based on random forest,’’ in Proc. IEEE 13th Int. Conf. Wearable Implant. Body Sensor Netw. (BSN), Jun. 2016, pp. 194–198.

[5] M. W. L. Moreira, J. J. P. C. Rodrigues, A. M. B. Oliveira, K. Saleem, and A. J. V. Neto, ‘‘Predicting hypertensive disorders in high-risk pregnancy using the random forest approach,’’ in Proc. IEEE Int. Conf. Commun. (ICC), May 2017, pp. 1–5.

[6] A. Hiwale, P. Talele, and R. Phalnikar, ‘‘Prediction of pregnancy-induced hypertension levels using machine learning algorithms,’’ Comput. Eng. Technol., vol. 1025, pp. 597–608, 2020.

[7] M. Flechet, F. Güiza, M. Schetz, P. Wouters, I. Vanhorebeek, I. Derese, J. Gunst, I. Spriet, M. Casaer, G. Van den Berghe, and G. Meyfroidt, ‘‘AKIpredictor, an online prognostic calculator for acute kidney injury in adult critically ill patients: Development, validation and comparison to serum neutrophil gelatinase-associated lipocalin,’’ Intensive Care Med., vol. 43, no. 6, pp. 764–773, Jun. 2017.

[8] V. Nagendra, H. Gude, D. Sampath, S. Corns, and S. Long, ‘‘Evaluation of SVM and RF classifiers in a real-time fetal monitoring system based on cardiotocography data,’’ in Proc. IEEE Conf. Comput. Intell. Bioinf.

Comput. Biol., Manchester, U.K., 2017, pp. 1–6.

[9] B. J. P. van der Ster, F. C. Bennis, T. Delhaas, B. E. Westerhof, W. J. Stok, and J. J. van Lieshout, ''Support vector machine based monitoring of cardio-cerebrovascular reserve during simulated hemorrhage,'' Frontiers Physiol., vol. 8, pp. 1–10, Jan. 2018.

[10] M. H. Hsieh, M. J. Hsieh, C.-M. Chen, C.-C. Hsieh, C.-M. Chao, and hbox{C.-C. Lai|, ''Comparison of machine learning models for the prediction of mortality of patients with unplanned extubation in intensive care units,'' Sci. Rep., vol. 8, no. 1, pp. 1–7, Nov. 2018.

[11] A. De Ramón Fernández, D. R. Fernández, and M. T. P. Sánchez, ''A decision support system for predicting the treatment of ectopic pregnancies,'' Int. J. Med. Informat., vol. 129, pp. 198–204, Sep. 2019.

[12] A. L'Heureux, K. Grolinger, H. F. Elyamany, and M. A. M. Capretz, ''Machine learning with big data: Challenges and approaches,'' IEEE Access, vol. 5, pp. 7776–7797, 2017.

[13] C. Wang, Z. Zhao, L. Gong, L. Zhu, Z. Liu, and X. Cheng, ''A distributed anomaly detection system for in-vehicle network using HTM,'' IEEE Access, vol. 6, pp. 9091–9098, 2018.

[14] J. Mackenzie, J. F. Roddick, and R. Zito, ''An evaluation of HTM and LSTM for short-term arterial traffic flow prediction,'' IEEE Trans. Intell. Transp. Syst., vol. 20, no. 5, pp. 1847–1857, May 2019.

[15] S. Ahmad, A. Lavin, S. Purdy, and Z. Agha, ''Unsupervised realtime anomaly detection for streaming data,'' Neurocomputing, vol. 262, pp. 134–147, Nov. 2017.

[16] Y. Cui, S. Ahmad, and J. Hawkins, ''Continuous online sequence learning with an unsupervised neural network model,'' Neural Comput., vol. 28, no. 11, pp. 2474–2504, Nov. 2016.

[17] J. Hawkins and S. Ahmad, ''Why neurons have thousands of synapses, a theory of sequence memory in neocortex,'' Frontiers Neural Circuits, vol. 10, pp. 1–13, Mar. 2016.

[18] S. Ahmad and J. Hawkins, ''Properties of sparse distributed representations and their application to hierarchical temporal memory,'' 2015, arXiv:1503.07469. [Online]. Available: http://arxiv.org/abs/1503.07469

[19] A. Pulver and S. Lyu, ''LSTM with working memory,'' in Proc. Int. Joint Conf. Neural Netw. (IJCNN), May 2017, pp. 845–851.

[20] K. Greff, R. K. Srivastava, J. Koutnik, B. R. Steunebrink, and J. Schmidhuber, ''LSTM: A search space odyssey,'' IEEE Trans. Neural Netw. Learn. Syst., vol. 28, no. 10, pp. 2222–2232, Oct. 2017.

[21] G. Ercolano, D. Riccio, and S. Rossi, ''Two deep approaches for ADL recognition: A multi-scale LSTM and a CNN-LSTM with a 3D matrix skeleton representation,'' in Proc. 26th IEEE Int. Symp. Robot Hum. Interact. Commun. (RO-MAN), Aug. 2017, pp. 877–882.

[22] I. Garcia-Magarino, R. Muttukrishnan, and J. Lloret, ''Human-centric AI for trustworthy IoT systems with explainable multilayer perceptrons,'' IEEE Access, vol. 7, pp. 125562–125574, 2019

[23] N. O. El-Ganainy, I. Balasingham, P. S. Halvorsen, and L. Arne Rosseland, ''On the performance of hierarchical temporal memory predictions of medical streams in real time,'' in Proc. 13th Int. Symp. Med. Inf. Commun. Technol. (ISMICT), May 2019, pp. 1–6.

[24] D. Kearney, S. McLoone, and T. Ward, ''Investigating the application of transfer learning to neural time series classification,'' in Proc. 30th Irish Signals Syst. Conf., Jun. 2019, pp. 1–5.

[25] J. Makhoul, ''Linear prediction: A tutorial review,'' Proc. IEEE, vol. 63, no. 4, pp. 561–580, Apr. 1975

[26] Fung, Teresa T., An Pan, Tao Hou, Dariush Mozaffarian, Kathryn M. Rexrode, Walter C. Willett, and Frank B. Hu. "Food quality score and the risk of coronary artery disease: a prospective analysis in 3 cohorts." *The American journal of clinical nutrition* 104, no. 1 (2016): 65-72.

[27] Conroy, Ronán Michael, K. Pyörälä, AP el Fitzgerald, S. Sans, A. Menotti, Gui De Backer, Dirk De Bacquer et al. "Estimation of ten-year risk of fatal cardiovascular disease in Europe: the SCORE project." *European heart journal* 24, no. 11 (2003): 987-1003.

[28] Escolar, Esteban, Guy Weigold, Anthon Fuisz, and Neil J. Weissman. "New imaging

techniques for diagnosing coronary artery disease." *Cmaj* 174, no. 4 (2006): 487-495.

[29] Braham, Roscoe R., J. Simpson, B. Ackerman, A. Betts, J. McCarthy, H. Orville, R. Ruskin et al. "Cloud physics—1974." *Bulletin of the American Meteorological Society* 55, no. 6 (1974): 543-586.

[30] Cullinane, A. B., P. S. Leung, J. Ortego, M. Coca-Prados, and B. J. Harvey. "Renin-angiotensin system expression and secretory function in cultured human ciliary body non-pigmented epithelium." *British journal of ophthalmology* 86, no. 6 (2002): 676-683.

[31] Goldschlager, N. O. R. A., ARTHUR SELZER, and Keith Cohn. "Treadmill stress tests as indicators of presence and severity of coronary artery disease." *Annals of Internal Medicine* 85, no. 3 (1976): 277-286.

[32] Rowland, Lewis P. "Biochemistry of muscle membranes in Duchenne muscular dystrophy." *Muscle & Nerve: Official Journal of the American Association of Electrodiagnostic Medicine* 3, no. 1 (1980): 3-20.

[33] Karthikeyan, Akshaya, Akshit Garg, P. K. Vinod, and U. Priyakumar. "Machine learning based clinical decision support system for early COVID-19 mortality prediction." *Frontiers in public health* 9 (2021): 626697.