Optimizing Telemedicine for Public Health: Novel Machine Learning-Driven Blood Pressure Evaluation Model

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KEYWORDS

Public health, telemedicine, healthcare, blood pressure (BP), prediction, fish migration optimized cat boost (FMO+CB)

ABSTRACT

As a form of asynchronous interaction between patients and doctors through electronic technology to provide distant clinical solutions, telemedicine seems not to deliver sufficient and accurate means of predicting and evaluating public health indicators outside conventional health settings like BP. In this investigation, we have used a new fish migration optimized cat boost technique named fish migration optimized cat boost (FMO+CB) for predicting blood pressure rates with the help of the physiological data collected from human subjects by the Electrical Impedance Myography (EIMO) apparatus. To further enhance the prediction performance of BP, the FMO technique and the CB method are incorporated. An analysis of the FMO approach shows that it is used to select the correct parameters to avoid overlearning. Evaluation of the prediction result of BP using various criteria such as MAE =3.06, MSE =50.04, and MAPE =3.03 are tested using the proposed approach through a Python platform. The experimental results prove the fact that the FMO+CB methodology has better prediction accuracy compared to the other methods.

1. Introduction

Telemedicine has emerged as one of the most critical tactical innovations in the healthcare service delivery system as it affords convenient remote monitoring and consultative service delivery. While exploring the area of public health, it is possible to use telemedicine for BP assessment as a unique opportunity to address hypertension, a leading cause of various cardiovascular diseases and a major concern to global health [1]. Some challenges that are likely to be encountered when using traditional BP monitoring methods include BP monitors are evaluated by contrasting digital (automatic) versions, like oscillometric monitors, with old (manual) techniques, like mercury sphygmomanometers. It evaluates measurement accuracy, usability, and dependability. While digital versions automate the procedure, traditional models rely on a healthcare expert to take manual readings [4]. This could lead to more consistent and convenient blood pressure monitoring patient adherence issues, measurement variability, and limitations of the availability of the equipment. These hurdles are surmountable, and through the adoption of telemedicine services, healthcare systems can deliver both remote, real-time control and monitoring of patients' BP [2]. When looking at how telemedicine can be incorporated into BP assessment, it is evident that the reduction in the frequency of face-to-face contact and hospital attendance will be found to have a positive impact on costs as well as increase patient compliance and outcomes [3]. Telemedicine is gradually becoming a necessity in today's healthcare institutions since its effectiveness in increasing BP checkups and consequently enhancing the health of the population is expected to advance [15]. Telemedicine can reduce the negative health impact, preserve the cost of healthcare, and enhance the availability of care, as technology may be used to achieve better BP measurement and control [12]. Therefore, it will be crucial to pursue the development and advancement of telemedicine for BP checking and its impact on public health to achieve optimal benefits as technology progresses [5].

In the study, we employed an FMO+CB technique to predict BP levels using the physiological data that the EIMO device collected from human patients.

2. Related works

Kadum et al. [6] developed the triage system for distant patients who utilize telemedicine and live far from hospitals by taking into account the differences in their chronic illnesses (diabetic, hypertensive, hypotensive, and heart disease). Furthermore, for patients who were remote, the outcomes of the machine learning-based remote triage framework in telemedicine (ML-ART) improve the efficacy of the e-triage structure and make accessible the possibility of future developments in telemedicine systems that would move the emphasis from remote monitoring to remote diagnoses. Lee et al. [13] introduced a tele monitoring (BPT) system that was Internet of Things (IoT)-based and AI-integrated, enabling people to monitor their BP at home [10]. The system, which had an F1 score of 98.5%, leverages machine-learning techniques to enable automatic digit identification. A cloud-based interface was created for automated data synchronization and risk categorization. Redefined the distinct telemedicine architecture framework in the environment of the Internet of Things, Albahri et al. [8] investigated several IoT-based telemedicine-related topics for the system, medical services, and applications [7]. The inquiry provided a broader basis for the market trends by looking at how IoT sensors, equipment, methodologies, and other technology assist telemedicine improvements for the management of various ailments. Katebi et al. [9] conquer the challenges associated with moving blood pressure data from oscillometric equipment to self-measured blood pressure surveillance platforms. By integrating this equipment into a therapeutic approach for blood pressure monitoring, 325 capture, and interaction with medical doctors, the management 326 of hypertension and cardiovascular conditions might be improved. The possibilities of artificial intelligence (AI) in healthcare were the major emphasis investigated by Ahmed et al. [14], with special attention to clinical support, diagnostics, telemedicine amenities, healthcare availability, and resource efficiency. The investigation demonstrated how AI was revolutionizing healthcare by highlighting how it could enhance telemedicine, improve diagnosis accuracy, personalize treatment regimens, and maximize the availability and efficiency of healthcare resources.

3. Methodology

The participants worked out for 35 minutes on a cycle ergometer set up in a sitting, upright position that was comparable to their resting posture. For fifteen minutes, participants cycled continuously at each of the three exercise intensities (20, 45, and 55 W). To give individuals time to cool down, the intensity was lowered to 15W for three minutes following a 35-minute workout. Throughout all other exercise phases, the EIMO gadget continually measured Photoplethysmography (PPG) and electrocardiography. During the workout session, twelve BP readings from the SunTech Tango were obtained every two minutes. Following the two-minute cooling-down phase, one last BP reading was obtained. Every BP reading was obtained using the right arm.

Fish migration optimized catboost (FMO+CB)

To improve model performance and guarantee reliable predictions, the method incorporates the FMO. Through the combination of these approaches, FMO+CB was able to assess BP with greater precision, providing a more advanced tool for medical diagnosis and healthcare management.

Fish Migration Optimization

FMO algorithm, the machine learning model's hyper parameters are optimized to increase the prediction's accuracy for BP rates. A novel swarm intelligence optimization algorithm called FMO. The two stages of the FMO algorithm replicate the grayling's migrating and swimming processes, respectively. The grayling's growth cycle. "0+" through "4+" stands for the grayling's five growth stages, from juvenile to adult. The grayling survival rate was shown by T. The probability of survival will rise in tandem with the grayling's ongoing growth, or $(T_1 < T_2 < T_3 < T_4)$. The percentage of graylings that go back to their original location to breed was represented by E. In a similar vein, when the grayling grows further, its rate of reproduction will also increase, going from $(E_2 < E_3 < E_4)$. Each person was represented in the FMO algorithm using the data structure provided in Equation (1).

$$W = < P, P_{pre}, Val, Eng, Phase > \tag{1}$$

Here each grayling individual was represented by W. P And P_{pre} stand for the person's previous and current positions, respectively. The fitness value determined by P was Val. The phase was a person's stage of growth. Energy was represented by Eng. The ability to migrate was stronger the higher the value. As the grayling continues to grow, the energy will eventually run out. During the first setup stage, Eng has been set to 2. The modified equation of Eng was provided by equation (2). j stands for the $j-th$ person.

$$Eng(j) = Eng(j) - \frac{Val(j)}{sum(Val)} \tag{2}$$

In actuality, the swimming technique mimics the grayling's foraging for food. Equation (3), used in the method, controls how each grayling advances in the solution space.

$$O_j^{new} = O_j^{old} + \frac{consumption*ori\_speed}{b+a*abs(ori\_speed)^w} \tag{3}$$

Where O_j^{old}or O_j^{new}stand for the $j-th$ individual's existing position and revised position, respectively. Three constants were $b, a,$ and w. They were configured in the FMO method, accordingly. Equation (4) displays the calculation method for random energy consumption during individual movement, which was referred to as $consumption$. The random number, parameter $q1$, between 0 and 1, and the maximum energy use of each movement, represented by E_max, was fixed at 2.

$$consumption = \begin{cases} q1 * F_{max}, if Eng(j) > E\_max \\ q1 * Eng(j), else \end{cases} \tag{4}$$

The formula for calculating ori_{speed} equation (5), where $q2$ was a random value between 0 and 1.

$$ori_{speed} = \begin{cases} O - O_{pref}, if\ q2 > 0.5 \\ P_{pre} - O, else \end{cases} \tag{5}$$

Some of the graylings were going to their original locations to breed new offspring once they reached adulthood. The FMO algorithm counts the total amount of people in each stage of the process first. Individuals that have growth stages of "0+" or "1+" can only update their growth stage because they are incapable of reproducing. Some people with developmental stages of "2+" and "3+" will go back to where they were born, while others will merely have their growth stage updated. Equation (6) will be used to update the position and set the $Phase$ to “0+” for those who are going back to their birthplace. The random integer in Equation (6) was $q3$, and the global best answer was O_{gbest}. People in the "4+" growth stage.

$$O = O_{gbest} + q3 * \left(O - O_{gbest}\right) \tag{6}$$

The above procedure improves the FMO algorithm's ability to tackle a wide range of challenging optimization issues.

CB

BP predictions are made by training the CB model with the optimum hyperparameters. The CB classification algorithm was used as a language-based tool for creating datasets to increase its performance, usability, and automatic processing of categorical information. Additionally, all BP categories of data can be converted into numbers without the need for specific pre-processing of the data. A useful machine language technique for handling complicated variables and diverse, noisy input was gradient boosting. Its robust features include a reduction in hyperparameter adjustment and a decrease in the likelihood of data overfitting. It employs binary tree models as base predictors. It concentrates on categorical variables and blends a gradient-boosting tree of decisions (GBDT) with categories.

$$C = \{(W_i, \Upsilon_j)\}; i = 1, \dots n \tag{7}$$

Where $W_i = (w_i^1, w_i^2, \dots w_i^m)$ was a vector with response feature and n features $\Upsilon_j \in Q$, a binary variable with values of 1 or 0, and a sample (W_i, Υ_j) that was independently and identically distributed according to an unknown distribution $O(.,..)$training a function $G: Q^m \to Q$ to minimize the anticipated loss given in the equation was the goal.

$$K(G) = EL\big(z, G(w)\big) \tag{8}$$

Where (W, z) was an example of test data taken from the training data C and $K(.,.)$ was an even loss function. By using all sample datasets in the algorithm for training, Cat Boost also contributes to the program's increased robustness. Before converting each sample's features, the goal value of a model was computed; weight and priority were applied. The CB classifier covers values that were missing for numerical parameters and non-encoded categories with little data preprocessing. The outcome of BP classification was evaluated using the classification accuracy as a criterion.

FMO+CB

The proposed combination of FMO+CB offers an improvement in the optimization process whereby the explorative characteristics of FMO are utilized for a better calibration of CB parameters. Such a strategy increases the reliability of the BP prediction models in the context of telemedicine. When FMO is applied to tuning CB parameters, the model is likely to perform better in the case of predetermining blood pressure levels, handling data imbalance, and increasing the overall score. It thus allows the establishment of a strong telemedicine system, whereby accurate and appropriate BP assessments can be made, hence the improvement of the overall health of the population, especially concerning hypertension.

4. Result and Discussion

The system features an Intel i5 13th Gen and runs on Windows 10 with 16 GB of RAM. Python 3.11 was used to execute the FMO+CB strategy and evaluate the method's efficiency. Our proposed FMO+CB strategy is evaluated with the existing methods such as Support Vector Machines (SVM) Artificial Neural Networks (ANN) and Long Short-Term Memory (LSTM) [11].

Accuracy

The reliability of the suggested method can be deduced from the accuracy of the forecasted results of BP for users, enhancing the diagnostic dependability. This ensures that the medical practitioners may be in a position to make informed decisions to improve the care of the patients. More efficient control of hypertension and related diseases is promoted by blood pressure monitoring through telemedicine, and such progress contributes to the enhancement of public health overall. The accuracy output is illustrated in the below figure 1.

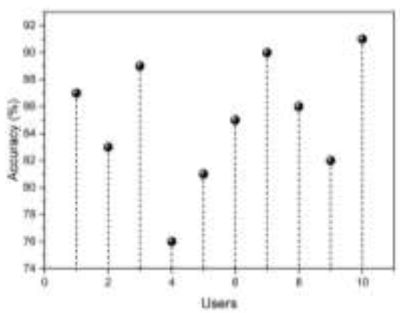

Figure 1. Accuracy output

Mean absolute error (MAE)

MAE determines how accurate the telemedicine system's public health predictions are, it computes the average absolute disparities between expected and actual values. The contrast of MAE is shown in Figure 2. Comparing our proposed FMO+CB approach to existing techniques like SVM, ANN, and LSTM, they performed 6.30, 9.06, and 8.63, while our approach performed 3.06. The results show that the recommended approach works better than the current techniques.

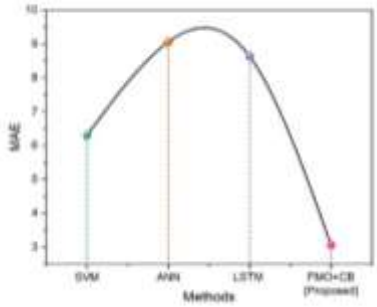

Figure 2. Output of MAE

Mean Squared Error (MSE)

MSE aids in evaluating the dependability of telehealth tools and algorithms in delivering accurate BP measurements for efficient patient care and public health administration. The MSE contrast is displayed in Figure 3. Our suggested FMO+CB approach scored 50.04 when compared to other methods like SVM, ANN, and LSTM, which scored 64.06, 123.53, and 115.47. The outcomes demonstrate that the suggested strategy perform well than the other methods.

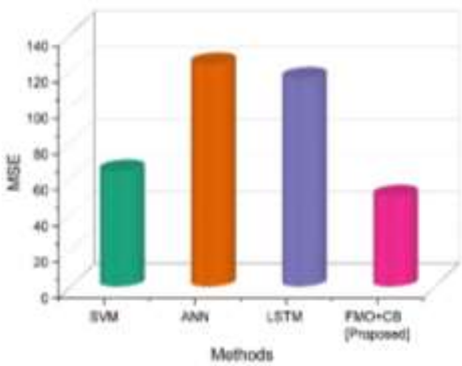

Figure 3. Output of MSE

Mean Absolute Percentage Error (MAPE)

It determines the average absolute percentage error, which sheds light on how accurate telemedicine systems are at managing public health by tracking and monitoring BP remotely**.** The contrast of the MAPE is presented in figure 4. It also differs from other methods like SVM, ANN, and LSTM that achieved 5. 26, 7.48, and 7.16 our proposed FMO+CB technique achieved 3.03. The results that are displayed reveal that the proposed technique has a lower as compared to the other methods.

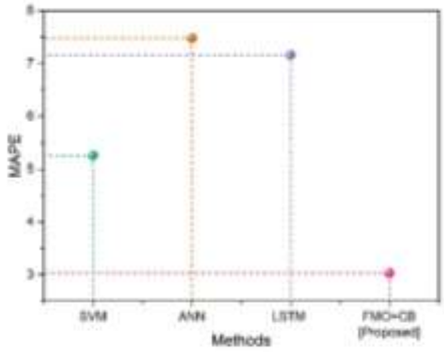

Figure 4. Output of MAPE

5. Conclusion

Thus, the current study contributes to the challenge of calibrating BP in telemedicine practices by employing an FMO+CB approach. Using the physiological data from human subjects through the EIMO apparatus, various parameters were tuned using the FMO method to curb the overfitting issue, while for the prediction of BP, and the CB method was tried. The FMO+CB framework performance was evaluated by the Python platform for all the metrics as MAPE (3. 03), MAE (3. 06), and MSE (50. 04) that stated this method has higher accuracy for prediction as compared to other methods. Based upon these results, the FMO+CB methodology holds promise in improving remote health monitoring in telemedicine applications as a viable means to predict BP outside of the conventional healthcare setting. This indicates that the generalizability of this model to different settings, to patients of different pathologies or ages, and in different healthcare delivery systems could be influenced by the quality and availability of data for this model and therefore its efficiency would differ. Future research may look at the raw data feed to improve the efficiency of BP monitoring. They suggested that the enhancements be possibly implemented which involve more health precautions and make the model applicable for several other groups so that the use of telemedicine in public health would be more efficient.

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