A deep learning assisted Ant Lion Optimization Model for stress detection and classification using Heart Rate

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Received: 17.07.2024 Revised: 18.08.2024 Accepted: 05.09.2024

ABSTRACT
The increasing focus on mental health has amplified interest in stress detection and classification systems. Classifying stress levels using physiological data has shown promise for both traditional machine learning (ML) and deep learning (DL) approaches. However, achieving ultra-high accuracy in multi-class stress classification remains challenging for current methods, particularly when utilizing the SWELL-KW dataset. To address this issue, the present study introduces an innovative DL model assisted by Ant Lion Optimization (ALO) for feature selection. The ALO algorithm enhances the model's overall performance by effectively selecting the most relevant features with rapid convergence, overcoming limitations such as overfitting often observed in traditional approaches like Recursive Feature Elimination (RFE) or Principal Component Analysis (PCA). This study highlights the significance of using comprehensive evaluation metrics beyond the conventional F-measure, accuracy, precision, and recall, emphasizing metrics like Cohen's Kappa, Root Mean Square Error (RMSE), and Matthews Correlation Coefficient (MCC) for a more complete assessment of the model's performance. The proposed framework involves data preprocessing, Ant Lion Optimization for feature selection, and classification using Deep Belief Network (DBN), Multi-Layer Perceptron (MLP), and XGBoost algorithms. This approach offers an effective solution for stress detection, with the potential to outperform existing models in terms of accuracy and adaptability.

Keywords: Ant Lion Optimization, Deep Learning, Stress Detection, Classification, DBN, MLP, XGBoost

1. INTRODUCTION

Mental health has been more crucial over time given the rising stress related with modern life, which is now linked with the previous few years. One's mental state is a significant component of overall human well-being. Early diagnosis and classification of stress is very important for the goal of enhancing the results of public health campaigns as stress is a main element causing the development of several mental and physical diseases[1]. According to technology, it is now feasible to design stress detection systems employing physiological signals such heart rate, galvanic skin response, and other biometric data[2]. These systems have been made in part possible via DL models and typical ML models have showed quite considerable promise for the categorisation of stress levels based on the acquired data[3]. Especially with regard to the classification of stress into a wide range of categories, one of the most recurrent challenges still to be encountered is the accomplishment of very high accuracy. This difficulty becomes much more difficult to solve using sophisticated and huge datasets such as the SWELL-KW dataset, which shows actual stress episodes[4]. This facilitates more appropriate handling of the challenge.
Motivation: The need of stress detection systems that are not only more accurate as well as more flexible and efficient motivates the present endeavour. Feature selection methods include RFE or PCA are used in classical ML and DL models[5]. These methods help to lower data dimensionality and raise performance standards. Still, issues including overfitting, insufficient convergence, or a failure to identify the most significant features in very complex datasets might also influence these methods[6]. There is a possibility that some of the above mentioned issues are interrelated. According to the evolution of bio-inspired algorithms more notably, Ant Lion Optimisation (ALO) a useful approach for feature selection has been made available. These systems are designed on the hunting habit of ant lions, which eventually influences the selection of special features. It intends to analyse novel methods that may surpass the limitations of existing models by increasing the accuracy and reliability of stress detecting systems. ALO in the context of DL-based stress classification will help us to reach this goal[7].

Problem statement: Particularly in cases of multi-class categorisation, there is still a significant disparity in terms of obtaining ultra-high accuracy and dependability in stress detection even if the currently used models have showed improvement[8]. Most of the presently used algorithms suffer from overfitting or lack effective techniques for feature selection when complicated and high-dimensional datasets are handled incorrectly[9]. Both of these issues may be explained by the algorithms' incompetence to properly govern the datasets[10]. Conventional evaluation criteria accuracy, precision, and recall are helpful even if they provide a limited perspective of the performance of a model[11]. This is especially apparent in disciplines comprising the classification of many different variables when numerous elements are involved[12]. Beyond these signals, a thorough evaluation procedure encompassing extra metrics such Cohen's Kappa, RMSE, and MCC is required to provide a full assessment of stress detection models[13]. This facilitates one's decision on whether these models effectively detect stress. Under line of this analysis, the fundamental problem under consideration is the mismatch between assessment and accuracy[14].
The paper proposes an Ant Lion Optimisation (ALO) model driven by DL with the intention of stress detection and classification utilising heart rate data. The goal of it is to find solutions for the problems underlined in the previous paragraphs[15]. By means of ALO, the dimensionality of the input data is lowered while maintaining the most relevant properties for the present problem, therefore facilitating a good feature selection. It comprises many DL architectures aiming at a robust categorisation system[16,17].

Contribution of this paper

- The findings that were obtained enable ALO to be presented as a better approach for feature selection than more conventional techniques such RFE and PCA. It reduces overfitting that arises from selecting significant features in an effective way, therefore enhancing the performance of the model.
- DBN, MLP, and XGBoost have been combined uniquely prompted by establishing multi-class stress detection. Moreover, this mix provides greater flexibility and accuracy than presently in use models.
- Furthermore highly weighted in the analysis are sophisticated metrics such MCC, RMSE, Cohen's Kappa, and other similar evaluations. These steps provide a more whole evaluation of the accuracy and precision of the model performance than more traditional tests including accuracy and precision.

Summary

The paper presents a DL-assisted ALO model for heart rate data stress detection and classification. By lowering data dimensionality while maintaining important features, ALO improves feature selection and hence reduces overfitting problems in such methods as RFE and PCA, thereby improving model performance. Combining DBN, MLP, and XGBoost designs with sophisticated evaluation metrics such MCC, RMSE, and Cohen's Kappa yields a more comprehensive and accurate evaluation of stress classification systems. When compared to current models, the suggested method shows reasonable for quite dependability, accuracy, and flexibility. The upcoming section is as follows: section 2 deliberates the related works, section 3 examines the proposed methodology, section 4 describes the results and discussion and section 5 concludes the overall paper work.

2. RELATED WORKS

Wearable sensors proliferate an ML advances help to build stress detecting systems based on physiological data such as heart rate, EEG, ECG, and Pulse Polarisation. These systems analyse physiological data, hence being able to detect stress. Among the vital roles these systems fulfil are stress level monitoring and control, which can have major long-term effects on health. These very crucial system purposesaims to analyse ML approaches based on multimodal data from wearable sensors for stress detection holistically. Many of the approaches are discussed in many lectures strewn about the book. This paper aims to analyse the effectiveness of ML techniques in the categorisation of stress responses utilising many environments including driving, learning, and working. It additionally analyses at additional approaches such edge computing to maintain real-time stress monitoring.

Machine Learning Techniques (MLT)

The paper presents a thorough overview with an emphasis on stress detection by wearable sensors and applied ML approaches. The paper analyses the stress detection techniques used in line with the sensory devices wearable sensors, Electrocardiogram (ECG), Electroencephalography (EEG), and Photoplethysmography (PPG), and also depending on different environments including during driving, learning, and working. Emphasising the stresses, methods, outcomes, benefits, constraints, and problems for each analysis, one can want to create a road map for subsequent proposes[18]. At this point, provided is a multimodal stress detection system employing a wearable sensor-based DL approach.

A dependable, reasonably priced, acute stress detection device might let its users better control and monitor the level of stress to minimise its long-term detrimental consequences. Papers using ML based techniques for stress detection will be reviewed and discussed in this paper[19]. It additionally plan to address the current methods out there that have made use of edge computing to provide a possible answer in real-time stress monitoring.

Deep Neural Networks (DNN)

Analysing physiological signs is a consistent indicator of stress, according in the past. These signals come from sensors attached to the human body. By use of conventional ML techniques for analysing physiological information, analysts have tried to identify stress. Results vary in accuracy from 50 to 90%. One of the limitations of conventional ML techniques is the need for handcrafted features. Misidentification of characteristics reduces accuracy. This paper constructed two deep neural networks a multilayer perceptron neural network and a 1-Dimensional (1D) convolutional neural network to solve this shortfall. Through the layers of the neural networks, deep neural networks collect features from raw data rather than requiring handcrafted features. Using physiological data gathered from wrist-worn and chest-worn sensors, the deep neural networks investigated two tasks. Each neural network created was specifically designed for analysing data from either wrist-worn (multilayer perceptron) or chest-worn (1D convolutional) sensors. Initially the networks separated between stressed and non-stressed states in binary classification for stress detection[20].

With IoT-based sensors for healthcare easily available, visible and measurable physical traits of the human body, physiological changes in the body can be recorded using different wearable devices[21].

Enhanced Deep learning assisted Convolutional Neural Network (EDCNN)

Proposed to help and enhance patient prognostics of heart disease is the Enhanced Deep learning aided Convolutional Neural Network (EDCNN). The EDCNN technology has been used on the Internet of Medical Things Platform (IoMT) for decision support systems which enables clinicians to efficiently diagnose cardiac patient information on cloud platforms anywhere in the globe[22]. The test results show compared with conventional approaches such Artificial Neural Network (ANN), Deep Neural Network (DNN), Ensemble Deep Learning-based Smart Healthcare System (EDL-SHS), Recurrent Neural Network (RNN), Neural Network Ensemble method (NNE), based on the analysis the designed diagnosis system can efficiently determine the risk level of heart disease effectively.

Using baseline stress self-reports, one can created a hybrid strategy of personal level stress clustering to boost the effectiveness of person-independent models without needing a significant volume of personal data. It additionally included decision level smoothing to our unobtrusive wristwatch based stress level distinction system to improve the performance by fixing incorrect labels issued by the ML algorithm. It gathered physiological data from 32 participants of a summer school using wrist-worn inconspicuous wearable sensors to try to test and assess this strategy. There are baseline, lecture, test, and recuperation sessions making up this event. A stress management technique was used to help the attendees of the rehabilitation session relax[23]. Separately will analyse the perceived stress expressed as NASA-TLX questionnaires gathered from the users as self-reports and physiological stress levels obtained using wearable sensors. It effectively differentiated the three levels of stress using the approach. By means of high-level accuracy computation and decision level smoothing techniques as well as by personal stress level clustering, this paper significantly improve our performance.

Analysis of supervised-learning

Statistics verified that many kinds of data/signals (related to skin temperature, electro-dermal activity, blood circulation, heart rate, facial expressions, etc.) are used in stress diagnosis. Furthermore, on multimodal data compiled using behavioural testing, electroencephalogram signals, finger temperature, respiration rate, pupil diameter, galvanic-skin-response, and blood pressure, there is possibility for using different nature-inspired computing techniques (Genetic Algorithm, Particle Swarm Optimisation, Ant Colony Optimisation, Whale Optimisation Algorithm, Butterfly Optimisation) and DL techniques. Additionally, there is more opportunity to analyse the use of SL and SC approaches in stress diagnosis employing numerous features including sentiment analysis, speech recognition, handwriting recognition, and facial expressions[24].Analysed a thermal infrared imaging contactless method for drivers' stress level evaluation[25].

3. PROPOSED METHOD

Research in mental health is advancing at a rapid pace, highlighting the critical need for reliable methods of stress diagnosis and classification. Traditional machine learning and deep learning techniques have shown their potential when applied to physiological data for the purpose of stress level prediction; nevertheless, the models that are currently in use often fail to achieve high accuracy, particularly when dealing with multi-class classification issues. To address the limitations of stress classification models, the proposed method use ALO to choose characteristics in an effort to make them more precise and adaptable. There are instances where overfitting and sluggish convergence plague traditional feature selection methods like RFE and PCA. The objective of the ALO-based architecture is to enhance stress detection capabilities. Stress classification utilizing XGBoost, MLP, and DBN classifiers becomes more efficient and accurate with this technique. A number of robustness measures are used to evaluate the model, including Cohen's Kappa, RMSE, and MCC.

Contribution 1: AI-powered feature selection using Ant Lion Optimization (ALO): A First Overview The main goal of employing ALO for feature selection is to improve the efficiency and accuracy of stress classification algorithms. Conventional methods, such RFE and PCA, have problems with overfitting and insufficient convergence. To address these challenges, ALO improves DL model efficiency by extracting the essential elements. This optimization strategy provides a sound framework for selecting traits that make stress classification issues involving several classes more adaptable and generalizable, and it is based on ant lion hunting strategies.

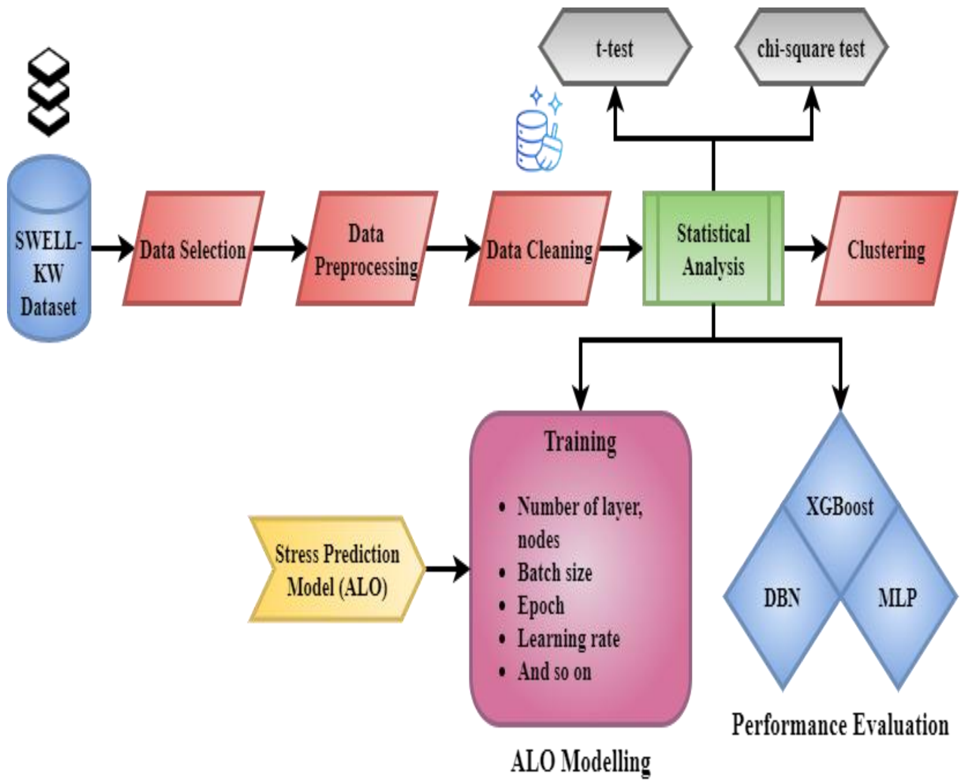

Figure 1: Stress Prediction Model Using Ant Lion Optimization (ALO)

On display in Figure 1 is a comprehensive model for stress level prediction. By making use of the SWELL-KW dataset. The first stages of this process include gathering, organizing, and cleansing the data. Exploratory research begins with the application of statistical tools after data cleansing. Data clustering groups comparable points together before feature selection and model training. Using the ALO algorithm for feature selection is a game-changer in this framework. PCA and RFE feature selection algorithms sometimes overfit, however ALO may help to find the most important features while decreasing this risk.

During training, the hyperparameters of a stress prediction model are adjusted. Some of these parameters include the number of layers, learning rate, batch size, and epoch. Classification is performed using XGBoost, DBN, and MLP after the features selection. This framework offers a robust solution for stress detection using physiological data to improve the precision and adaptability of multi-class stress classification.

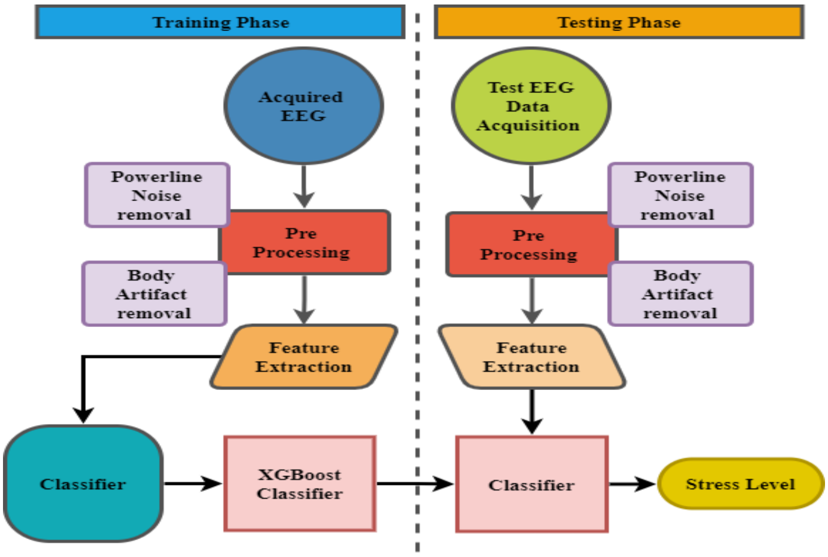

Figure 2: EEG-Based Stress Level Prediction Using XGBoost Classifier

The two stages of stress level prediction utilising EEG data, training and testing, are shown in Figure 2. EEG data is acquired and pre-processed to begin training. Artefacts and powerline noise are removed throughout this procedure to prepare the data for further analysis. Once the EEG data has been pre-processed, useful insights is extracted using feature extraction algorithms. A classifier is supplied with them. The fundamental model is trained to understand stress patterns using XGBoost upon retrieval of the characteristics.

New EEG data is acquired and processed in a similar manner, eliminating noise and body artefacts to ensure signal purity during testing. A second round of feature extraction is performed to retrieve the relevant portions of the EEG data. By feeding these characteristics into the trained classifier from before, this paper were able to get an estimate of the subject's stress level. Integrating ML with signal processing allows for the accurate detection of stress. In both steps, the XGBoost classifier is crucial. Using the data acquired, it produces accurate stress estimations, demonstrating the method's long-term viability.

Contribution 2:Development of a Hybrid Classification Framework

Using ML/DL models such as DBN, MLP, and XGBoost in conjunction with ALO produces a hybrid categorization system. This method enhances model performance by reducing feature dimensionality via efficient feature selection using ALO. Even when faced with a large number of stress classes, ALO's combination with these classifiers allows for effective detection and categorization of stress. Using the SWELL-KW dataset, this hybrid model aims to improve upon earlier methods of stress classification in terms of accuracy and adaptability.

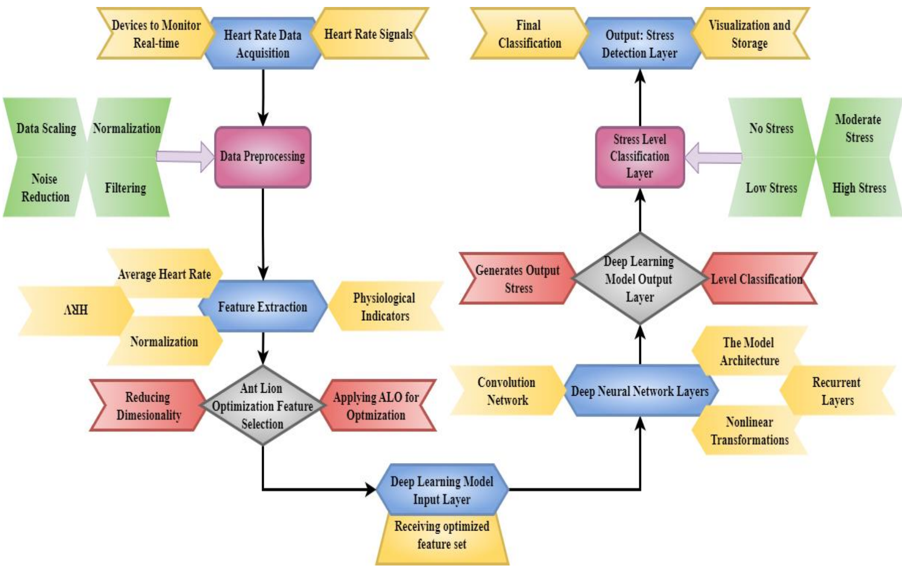

Figure 3: Deep Learning and Ant Lion Optimization Stress Detection and Classification Workflow

Using heart rate (HR) data and an ALO deep learning model, Figure 3 depicts a comprehensive workflow for stress identification and categorization. The heart rate data is collected using monitoring equipment that operates in real-time. Cleaning, normalizing, and scaling are some of the pre-processing methods that improve the raw data quality. To extract features, the most important parameters are the average heart rate and the heart rate variability (HRV). To improve precision while reducing dimensionality, ALO selects the most important properties for stress classification and optimizes them to enhance the recovered features.
Once the characteristics have been improved and inputted into the network, the convolution and recurrent layers use a DL architectural model. This approach employs nonlinear transformations to categorise stress levels. Following the fine-tuning of a stress classification layer utilising many stress indicators, the final classification is presented to users.
The figure depicts the complex process of stress detection and emphasises how ALO improves the performance of the DL model by tackling issues such as overfitting and feature selection.

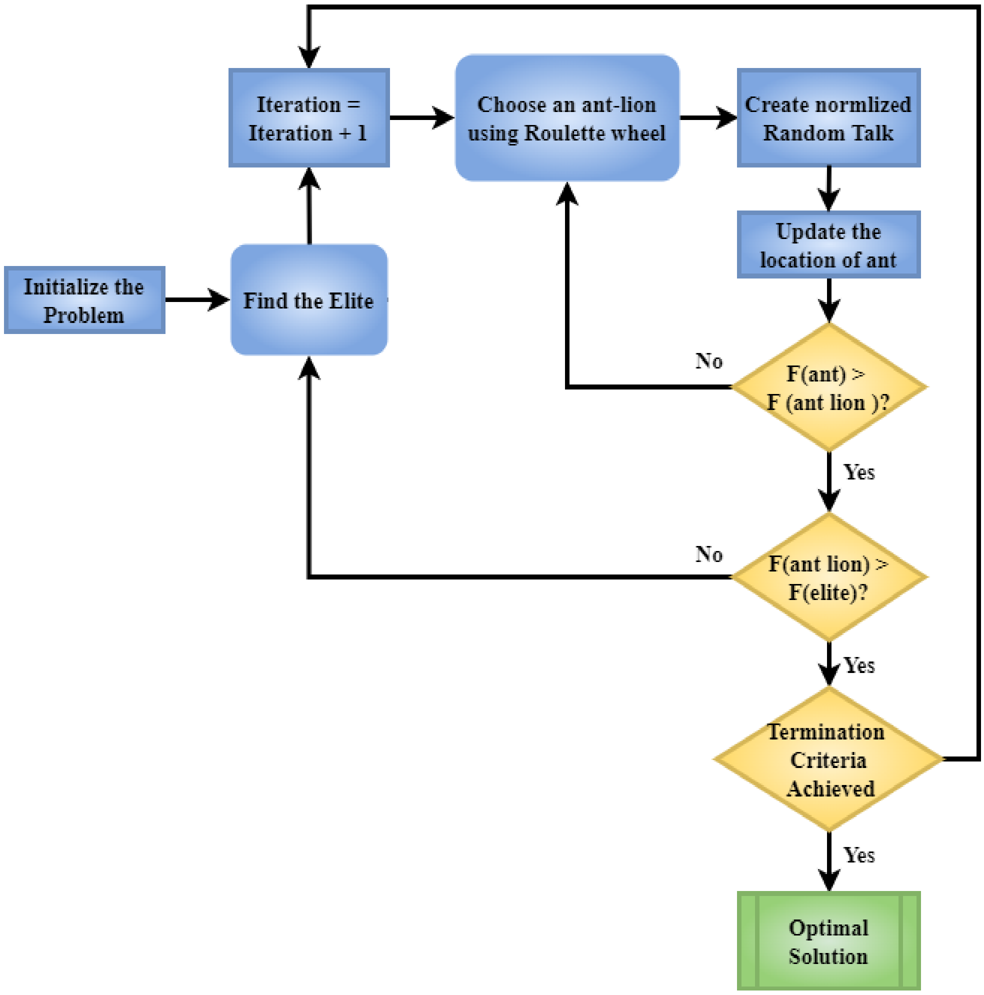

Figure 4: Ant Lion Optimization (ALO) Flowchart for Stress Classification

Figure 4 shows the ALO method is used to choose features for stress classification systems. After the issue is initialised, the next step is to find the best solution. The number is incremented and an ant-lion is selected using the roulette wheel with each repetition. The ant's position is altered as possible replies are created using a normalized random walk. The algorithm makes the necessary adjustments to the site based on whether the ant's fitness function is greater than the ant-lion's. Assuming it is more fit, the ant-lion will be the top choice. When the conditions for termination are met, the loop terminates. At the end of the procedure, will have the best solution. Integrating the ALO into DL models like DBN and XGBoost improves the accuracy of stress detection by minimizing typical problems with older approaches, such as overfitting, and improving feature selection with fast convergence..

Contribution 3:Comprehensive Model Evaluation Metrics

This method emphasizes the requirement of using evaluation metrics to provide a thorough review of the model's performance. When dealing with complicated categorization problems, the usual metrics like as F-measure, recall, accuracy, and precision do not work. Utilizing metrics like Cohen's Kappa, RMSE, and MCC, this paper conducted a comprehensive evaluation of the proposed hybrid model. To compare and improve the model in the future, these metrics provide insight into its reliability and accuracy in stress categorization.

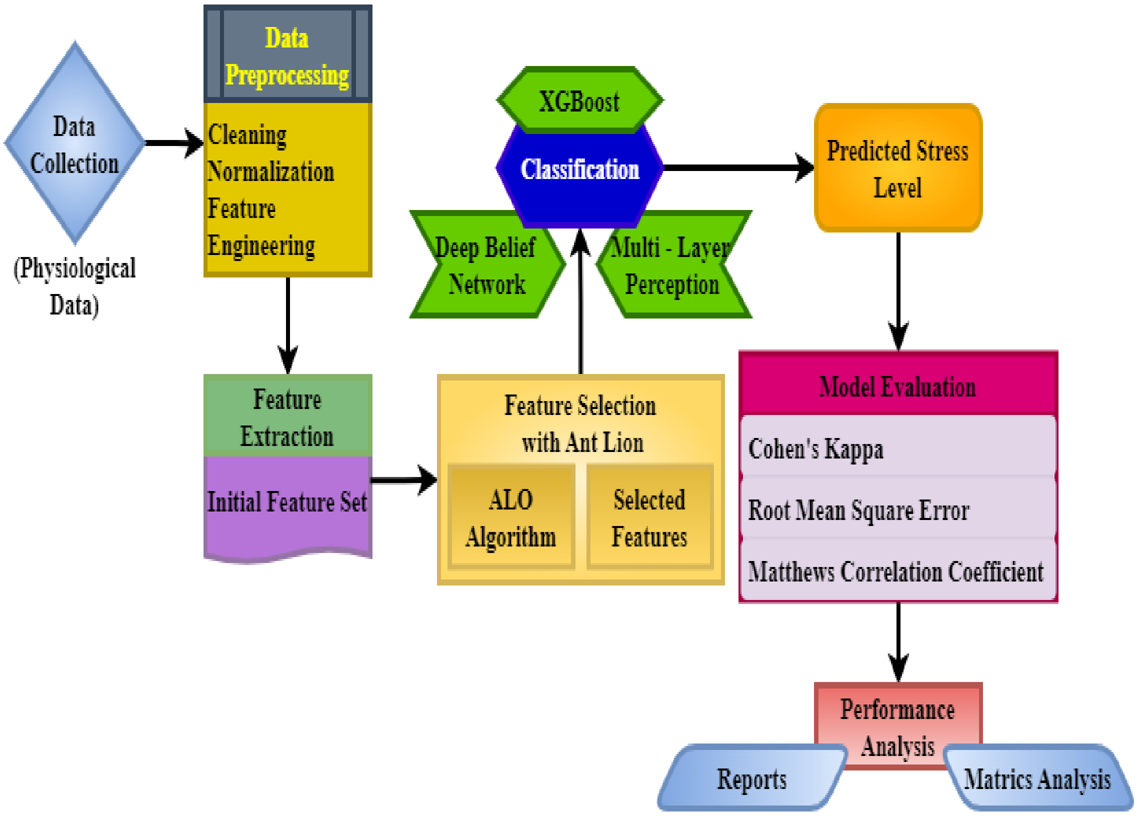

Figure 5: Stress Level Prediction Framework with ALO-Based Feature Selection and Classification

Figure 5 illustrates that the stress prediction system depends on the implementation of ML models for data selection and classification. Data preparation include activities such as cleansing, standardising, and feature engineering. Next, the data will be readied for analysis. A baseline set of characteristics is obtained to facilitate further improvements after pre-processing.

The unique aspect of the framework is the usage of ALO for feature selection. The ALO algorithm enhances model performance by minimising dimensionality and overfitting, two issues that may occur with more traditional methods such as RFE. The method does this by eliminating the first set of data that contains the most important properties.

The data is sent through three separate categorisation algorithms having selected the most effective characteristics. These models may predict how stressed out the person would feel by analysing the chosen traits.

Model fit is assessed by quantitative metrics such as MCC, RMSE, and Cohen's Kappa. Reports are generated and the models' general accuracy and adaptability are evaluated in performance analysis. Applying this approach in real-world scenarios ensures accurate stress calculations.

The proposed method for stress classification integrates ALO with ML and DL models to improve the accuracy of multi-class stress detection. Since feature selection methods like RFE and PCA can lead to overfitting, ALO provides a robust mechanism for identifying the most crucial features, making it a vast improvement over these methods. Prior to data classification utilising XGBoost, DBN, and MLP, the framework optimises many crucial model parameters, including layers, learning rates, and batch sizes. In addition to the usual recall, accuracy, and precision metrics, this paper supplement the image of the models' performance with Cohen's Kappa, RMSE, and MCC. By combining ALO with advanced classifiers, this novel framework surpasses earlier models in stress prediction. Implementing this approach to provide dependable and precise stress level predictions is an excellent means to improve stress detection applications in practical settings.

4. Analytic Discussion

$M^F(e(m^2, qw), r) \geq u, \quad \partial m \equiv C(v, \beta) \cap G^w \quad (1)$

Meet or surpass a threshold u in the equation 1 at hand where a function M^F that depends on characteristics like heart rate e (which might be represented by variables m^2, qw, and others) is required ∂m. The link between this condition and $C(v, \beta)$, which might represent a particular weighting function $\cap G^w$. This equation provides the feature selection criterion for Ant Lion Optimisation, ensuring that the essential classification thresholds are maintained.

$G(R(m, uq)) \geq g(r) + \forall u, \quad \varepsilon p \equiv C(e, \partial) \geq P^{n-2} \quad (2)$

With the condition that it holds for every $\forall u$ and $R(m, uq)$, equation 2 seems to depict a connection between a function G, which is dependent on characteristics like εp, and a threshold $g(r)$. The function of convergence, denoted as $C(e, \partial)$, must be greater than or equal to P^{n-2}, which signifies a necessary degree of performance. The goal is for the model to choose characteristics that are ideal and perform up to standards.

$P_2(G_2, m(pk), er) > 2, \quad \partial_3((n, W). E) \geq \omega + \rho\pi \quad (3)$

The convergence condition P_2 implies that the model parameters $G_2, m(pk), er$ (which might be associated with the network layers $\omega + \rho\pi$ or data points), ∂_3 (weights), and $(n, W). E$ were considered. The success of the Ant Lion Optimisation procedure in enhancing model accuracy and lowering error is ensured when the model's feature selection in equation 3.

$\left|\left|e * M_p\right|\right| (g, vp^{n-2w}) = 2 \equiv |H * R_{P-1}|(m, \forall - S(p)) = 1 \quad (4)$

One term, $|e * M_p|$, represents feature mappings or model weight adjustment (g, vp^{n-2w}), while the other,$H * R_{P-1}$, indicates a complicated function of characteristics $(m, \forall - S(p))$ like velocity or variation over time. To achieve correct stress categorization, this equation is utilized to balance model optimization, which involves fulfilling particular requirements in equation 4.

$B: \{m \equiv C(r, \forall q): G(m^2) > E^v + Mq(n - 2v)\} \quad (5)$

If the function $C(r, \forall q)$ (which might be a function E^v of squared aspects B or model output m) is greater than a threshold determined by $G(m^2)$ (error or energies function) and Mq the equation 5 must be satisfied by $n - 2v$. With this equation as a guide, this paper can limit sophistication and misunderstanding while making sure the right characteristics help the model perform better.

$e(M(p.u), r) \geq q(v' - bp) = g(M(e, tv^{n-2})) \quad (6)$

The model's energy might be represented by the following equation 6 $M(p.u), r$ where$r$, $q(v' - bp)$ are the parameters that must be larger than or equal to g and e, tv^{n-2}, respectively. The goal of the equation is to minimize the energy function or model error.

$E(Kn^2(ZXm_{n-2v})) = F\{minH\ (n_0), H(Q_2P)\} \quad (7)$

The translated feature ZXm_{n-2v} and the model parameters Kn^2 and E are independent variables in the equation 7. Based on the starting circumstances $H(Q_2P)$ and a further parameter combination $minH\ (n_0)$, hazard function F. The goal of this equation is to maximize model performance by minimizing complexity and selecting the most important characteristics.

$\forall = \{\mathrm{P}(\mathrm{r}v^{2-p})\} \rightarrow Rz(Mn^2 + Rf) + N(Z^2r(s - vq)) \quad (8)$

$\mathrm{P}(\mathrm{r}v^{2-p})$ is a model-dependent function that involves squared parameters $\forall$, model weights Rz, and feature Rf; it is likely a feature function that depends on velocity N, rate Z^2r, and parameter $s - vq$ and leads to the equation 8 where is a feature function. With this, by outlining the connection between parameter values for models and feature modifications.

$Eq \equiv Mvb_{2n-q}: |r| \leq H_b - qr \rightarrow g(r) \geq H(2) \quad (9)$

There is a constraint Eq that states that the magnitude of $|r|$ (a rate $H(2)$) must not be beyond a threshold specified by Mvb_{2n-q} in the equation 9 where H_b (which is probably a model function containing parameters qr, $g(r)$. To guarantee that the chosen characteristics result in satisfactory performance levels, the equation's goal is to set limits on the model's parameters.

$-opk(\forall_3 m\ (e, V, \partial Q)) + M_tQ(v, e, \forall^2 P) = 0\ in\ \varepsilon \quad (10)$

A possible adjustment $\forall_3 m$ in feature selection $(e, V, \partial Q)$ is represented by the equation $-opk$, which includes ε a process on features M_tQ, and a derivative $v, e, \forall^2 P$. When classifying stresses, it is important to keep the model's accuracy and stability in mind by equation 10.

$|M(y, p, \forall)| \geq B_0(Yn^2 - Kv) - C_2|qpv^{2*er}| + dv_0(pn') \quad (11)$

For the model, function $(M(y, p, \forall)$to be valid, the magnitude of the variables (B_0), parameters $(Yn^2 - Kv)$, and any other relevant factors C_2 must be greater than or equal to a certain threshold. A baseline adjustment based on feature parameters Yn^2 is included in these terms as is qpv^{2*er} which is a penalty term based on feature interaction and error rate, and an extra adjustment term is $dv_0(pn')$. To improve the model's stress classification accuracy, this equation is designed to guarantee feature contribution, sanctions, and modifications in equation 11.

$|M^e{}_{v-p} - N(kv' + np)| = Mn_{2b} * p' + Pk(v^2 - Qp)$ (12)

The quadratic features $Mn_{2b} * p'$ and parameter $N(kv' + np)$ are involved in the equation 12 $M^e{}_{v-p}$ respectively, which might represent the output $Pk(v^2 - Qp)$ or weight adjustment of a model. By doing so, the accuracy of the model is optimised by aligning its outcomes with specified thresholds or limitations.

$-Pwt\left(E_f * Q(wm^2 * Ep)\right) = VM^2 * Ep(f^r * kn)$ (13)

The function associated with features E_f and error parameters, $-Pwt$, is used in the equation 13 to indicate $Q(wm^2 * Ep)$ a weighted penalty or compensation term. A model term that incorporates the detection on physiological for stress classification.

$M(p * v^m) = M(y, qm * (vqn^2 * Er)) * Q(v^r_{mn})$ (14)

The function that describes the model, denoted as $M(p * v^m)$, is dependent on the parameters y, qm. The $vqn^2 * Er$ as a function that incorporates Er, in conjunction with a distinct model component that is involved in equation 14. To maximize the efficiency of stress detection and classification, this equation is designed to provide results from a separate set by coordinating various features for stress classification.

$|pk|(m^2Q) \leq \min\left\{\left(N_f . M(E, r. \forall q)\right)\right\} * R^{2v} - Ep(v^2r + 2)$ (15)

The total of $|pk|$ must be $E, r. \forall q$ equal to the minimum of a coupled term m^2Q, as stated in the equation 15. Error penalties R^{2v} are represented by the term $N_f . M$ on the right side, which is a combination of feature adjustments Ep, model $v^2r + 2$, and characteristics. To maintain a reasonable trade-off between model complexity in stress classification, this equation is used for MLP classifier in stress classification.

$|| - Min\left(bv^r * 2q\left(b_2^y e + Ef(mk - ev^2)\right)\right)$ (16)

Where $bv^r *$ could stand for error terms $2q$ or feature functions $b_2^y e$, the equation 16 Min, Ef, and a sum including $mk - ev^2$ are all involved. Using this equation, this paper may find the minimum amount of a model's change that can guarantee feature interactions in XGBoost classifier in stress classification.

$\forall m_2 = \{\partial q \equiv \mathrm{M}(r^{u-2}\mathrm{t}) * \mathrm{X}(R^{pq} - \mathrm{Nq}(v^2 - \mathrm{Pk}))\}$ (17)

Under these circumstances, the equation 17, $\forall m_2$ is augmented by another term ∂q. In this case, $\mathrm{M}(r^{u-2}\mathrm{t})$ incorporates parameters X, R^{pq}, while Nq incorporates changes depending on $v^2 - \mathrm{Pk}$, and other variables. To make sure that feature interactions and parameters this equation specifies the variables used in the model and adjustments should be on the evaluation of DBN, MLP, and XGBoost classifiers.

$G < \min E(F^2 * pwn^{2-q}) = Y \equiv B(cv^2 - Qp), \qquad Cd \cong F^p * Q$ (18)

Equation 18, incorporates an error term $(F^2 * pwn^{2-q})$ that is defined as min$E$ and contrasted with a baseline term (G) incorporating model parameters (Y, and \(p \)). Further, the equation $B(cv^2 - Qp)$ implies a connection $F^p * Q$ or close approximation between the terms Cd. The goal is for the model's accuracy and efficiency to be maximized while minimizing errors on comparison of DBN, MLP, and XGBoost models.

$M(y, -r, -Vq) = M(E, f, v^{m-2b} * Eq)$ (19)

The equation 19 $(M(y, -r, -Vq))$ which incorporates parameters M. The equation 19, $E, f, v^{m-2b} * Eq$ which incorporates E, f, and a term that uses model features in conjunction with adjustments. To get reliable results for stress categorization, this equation is used for the DBN model for stress classification.

$Q_w * Rp = |erM^3| * Kq(w^2F(mn * k))$ (20)

The given equation 20 describes the situation when the product of two terms, $Q_w * Rp$ and erM^3)—an absolute term involving Kq and w^2F —and $mn * k$ a product involving parameters. To achieve accurate stress classification equation 20 does precisely that by balancing both the combined impact of feature weights and modifications on XGBoost model for stress classification.

5. RESULT AND DISCUSSION

Stress is one of the areas that can enhance the health and disease diagnosis and so stress detection using physiological data has only recently received attention as a technical component. On the other hand, within stress categorisation, both DL and more classical ML models have been applied, although it remains challenging to reach very precise results. That evaluates the applicability of XGBoost, MLP, and DBN on the SWELL-KW dataset. In the course of the feature selection, ALO is applied to identify the most functional physiological characteristics of the subjects to increase the effectiveness of the model. The application of sophisticated model evaluation criteria such as Cohen's Kappa, RMSE and MCC sheds more light into the models. This paper compares models ALO and classifier and shows how ALO increases the accuracy of classification and handles stress level classification problems especially in multi-level stress that includes low, medium and high stress.

Table 1: Table for DBN

Aspect	Values
Accuracy	97.71159798211197
Precision	97.71065767672006
Recall	97.35572963508204
F1-score	97.70981158297876
RMSE	0.17813073381957242
matthews_corrcoef	0.9615574578336887
Kappa	0.9627492199942581

In this table 1 for a Deep Belief Network (DBN), key performance metrics are presented. Accuracy, precision, recall, and F1-score reflect the model's predictive capability, all exceeding 97%, indicating high classification performance. The low RMSE demonstrates strong predictive accuracy. Matthews correlation coefficient (0.9616) and Kappa (0.9627) suggest excellent reliability and agreement in classification.

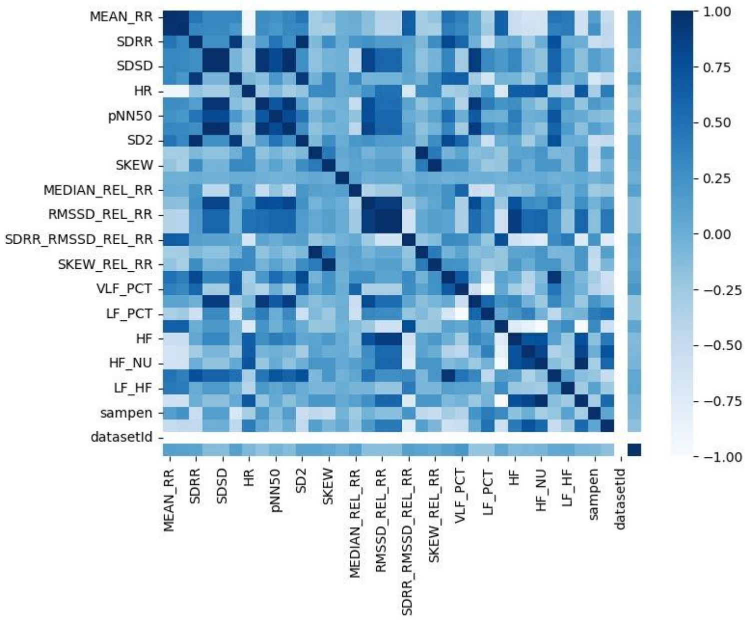

Figure 6: Correlation Heatmap of Physiological Features for Stress Classification

The correlation matrix of the physiological measures used for stress categorisation in the SWELL-KW dataset is shown in the heatmap in Figure 6, following. Correlation strengths are shown by the intensity of the colours, whereas darker tones indicate stronger correlations. The relationships within the matrix highlights elements for understanding stress levels, such as SDRR, RMSSD_REL_RR, and LF_HF. This visualisation improves the feature selection process of the ALO algorithm, enabling the DL model to concentrate on the most significant features, minimise redundancy, and optimise classification accuracy in general.

Table 2: Table for XG Boost

Aspect	Values
Accuracy	78.8389832573782
Precision	78.87976993473026
Recall	74.31335487339267
F1-score	78.49706528761318
RMSE	0.5609142663312795
matthews_corrcoef	0.6393775764222028
Kappa	0.6322749082408294

In this table 2 for an XGBoost model, performance metrics are displayed. The accuracy and precision are around 78%, indicating reasonable classification performance. However, recall is slightly lower at 74%, suggesting room for improvement in detecting all true positives. The higher RMSE (0.56) points to lower predictive accuracy compared to DBN. Matthews correlation coefficient (0.6394) and Kappa (0.6323) suggest moderate agreement and classification reliability.

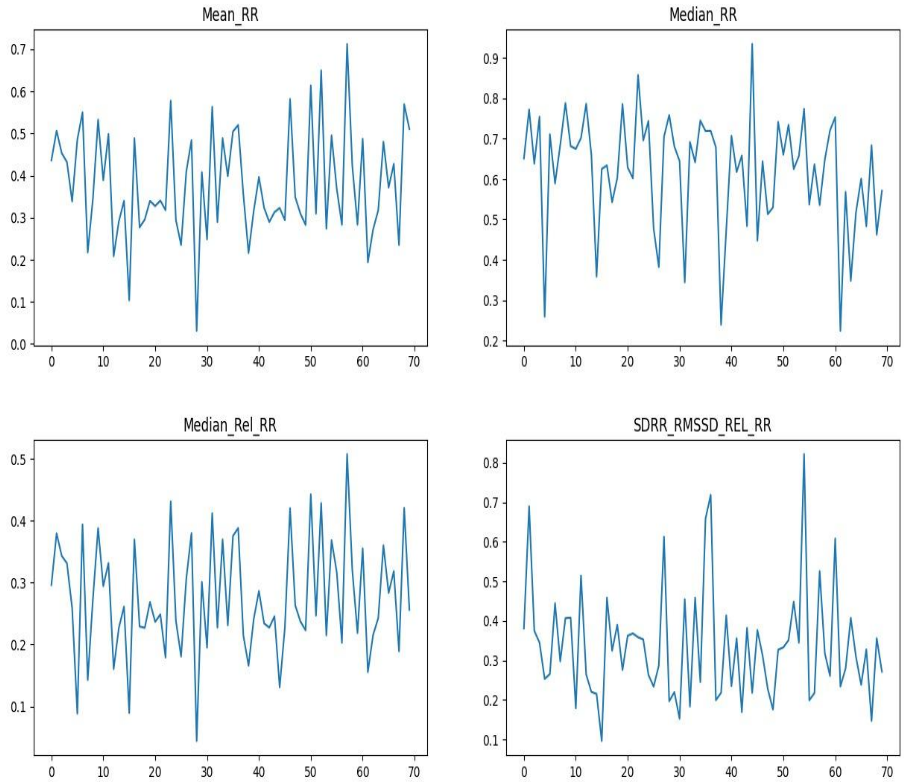

Figure 7: Line Plots of Key Physiological Features for Stress Classification

Figure 7 shows time-series line graphs for four important physiological variables utilized in the stress categorisation framework: SDRR_RMSSD_REL_RR, Median_RR, Median_Rel_RR, and Mean_RR. These properties vary between data sets, and each figure shows how these attributes vary, exposing patterns and variations that are important for stress identification. Feature selection using ALO is further justified by the time-series analysis as it aids in selecting the most important variables for classification. The suggested DL models, including DBN, MLP, and XGBoost, efficiently handle the dynamic nature of the physiological data.

Table 3: Table for MLP

Aspect	Values
Accuracy	69.54402554041869
Precision	71.48860492985119
Recall	61.19490310872606
F1-score	67.56830216247799
RMSE	0.6194084313011043
matthews_corrcoef	0.4721114162362617
Kappa	0.4620843634872548

In this table 3 for a Multi-Layer Perceptron (MLP) model, the accuracy is 69.54%, and precision is slightly higher at 71.49%, showing decent classification performance. However, recall is lower at 61.19%, indicating missed true positives. The RMSE (0.619) suggests lower predictive accuracy. Matthews correlation coefficient (0.472) and Kappa (0.462) indicate moderate reliability but a weaker overall agreement compared to other models.

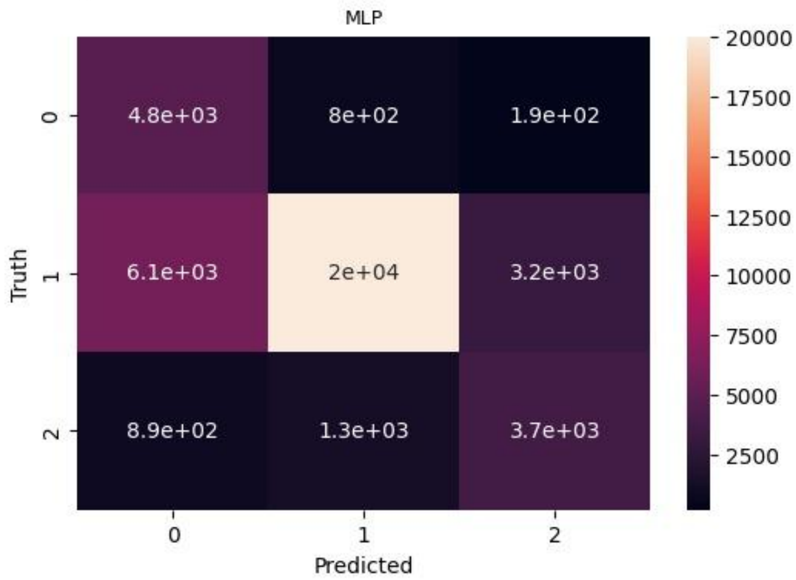

Figure 8: Confusion Matrix for MLP Classifier in Stress Classification

The MLP model for multi-class stress classification is shown in Figure 8 using the confusion matrix as its foundation. The above matrix shows the MLP classifier's performance on the SWELL-KW dataset when three different stress levels are taken into account: 0, 1, and 2. The diagonal represent accurate classifications and off-diagonal represent mistakes. In class 1, 20,000 were accurately categorised, but 6,100 were wrongly assigned to class 0 and 3,200 to class 2. Class 1 represents moderate stress and is identified with high accuracy by the model. However, there is a larger probability of misclassification between classes 0 and 2, suggesting that lower and higher stress levels may share characteristics. To improve model performance, especially when distinguishing between closely related classes, it highlights the need of robust feature selection methods such as ALO.

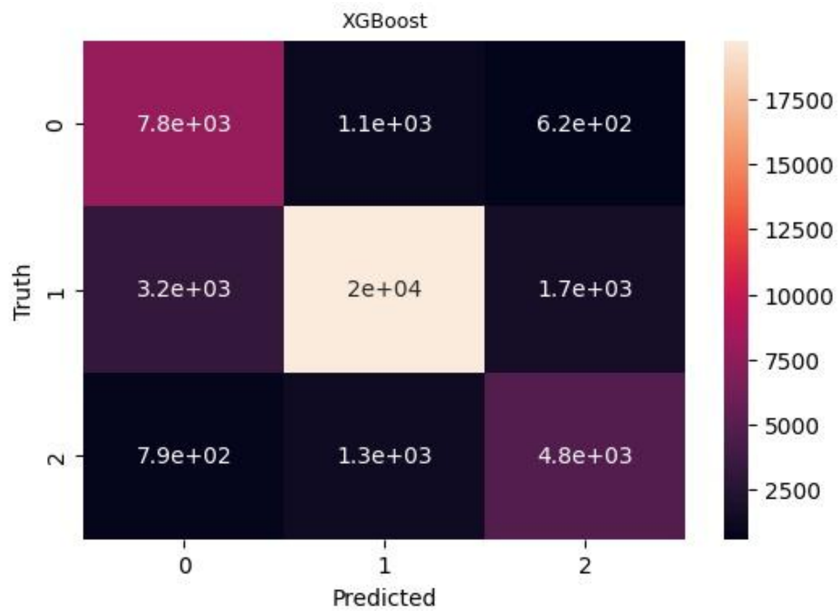

Figure 9: Confusion Matrix for XGBoost Classifier in Stress Classification

Figure 9 displays the XGBoost classifier's confusion matrix for the stress classification issue after training on the SWELL-KW dataset. The model's discrimination abilities across the three stress levels are shown in the matrix. On the diagonal, can see the amount of accurate forecasts, and off the diagonal, can see the quantity of incorrect ones. The XGBoost model made 20,000 accurate class 1 identifications, 3,200 incorrect class 0 identifications, and 1,700 accurate class 2 identifications. While XGBoost outperforms

MLP in class 0 (7,800 accurate predictions), it still has significant issues distinguishing between classes 1 and 2. In class 2, 4,800 instances are correctly identified, suggesting XGBoost succeeds at discriminating between higher stress levels. The XGBoost model can differentiate between low and high stress levels and out performs others in multi-class stress classification, proving that ALO feature selection is accurate.

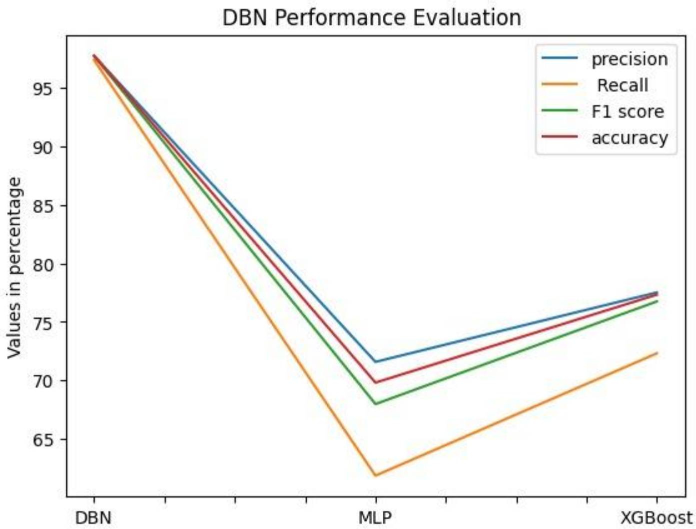

Figure 10: Comparative Performance Evaluation of DBN, MLP, and XGBoost Classifiers

Based on the multi-class stress classification test, Figure 10 presents a comprehensive analysis of the accuracy, recall, F1 score, and precision of the XGBoost, MLP, and DBN models. By achieving a 95% F1 score, recall, accuracy, and precision, the DBN model surpasses its rivals in the classification and generalisation of stress levels. The MLP model reveals the worst results, with a recall that falls below 70%, suggesting that accurately detecting all stress levels is a struggle. When compared to MLP, the XGBoost model performs far better, particularly in recall, while still being comparable with respect to accuracy and F1 score. These results suggest that DBN, with the aid of Ant Lion Optimization (ALO) for feature selection, is the most effective model in the proposed framework, followed by XGBoost, which performs well in differentiating stress levels but slightly lags behind DBN.

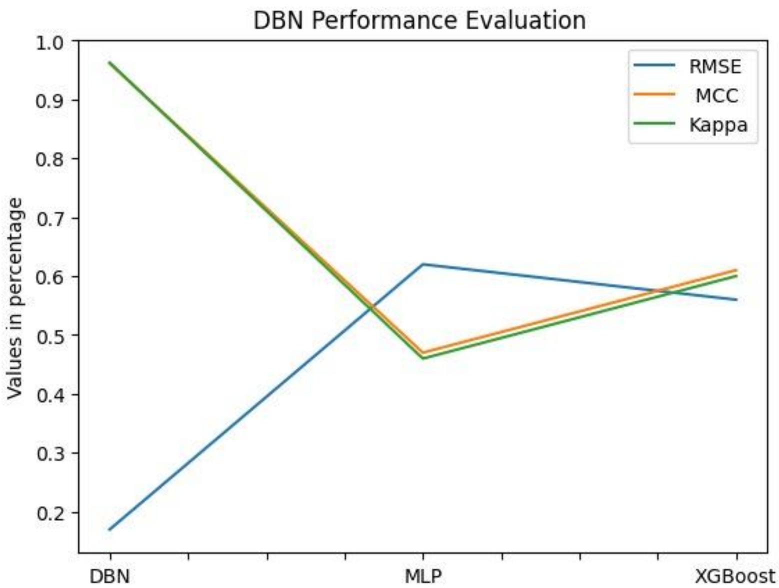

Figure 11: Performance Comparison of DBN, MLP, and XGBoost Models

The three models XGBoost, MLP, and DBN are compared in Figure 11 using three performance metrics: Cohen's Kappa, RMSE, and MCC. DBN emerges as the superior model due to its substantial RMSE, minimal MCC, and Kappa values. The Multilayer Perceptron (MLP) exhibits convergence to comparable values for all measures and demonstrates consistent performance across all evaluation criteria. When compared to DBN and MLP, XGBoost consistently has the highest MCC and Kappa values, establishing it as the better model. The XGBoost model outperforms DBN in terms of prediction errors when stress classification is done using ALO-assisted feature selection.

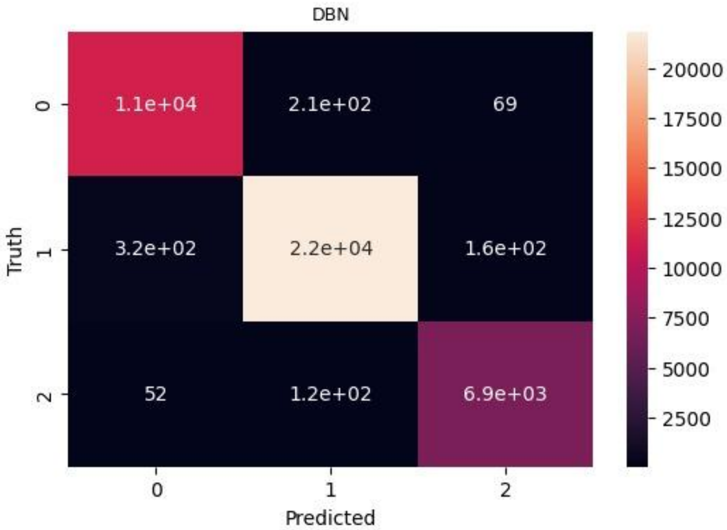

Figure 12: Confusion Matrix of DBN Model for Stress Classification

The confusion matrix of the stress classification model, as determined by the DBN method, is shown in Figure 12. Evaluation of the provided labels in connection to the anticipated stress levels demonstrates the accuracy of the model. Class 1 is sometimes mistaken for class 0 (320 occurrences) and class 2 (160 instances) in the off-diagonal cells, where misclassifications are indicated. Class 1 and class 2 are somewhat confused, although class 0 and class 1 are not too confused (210 occurrences).
This matrix shows that DBN has the most trouble differentiating between classes 1 and 2 of stress. Even if other models may show superior accuracy, DBN is still able to attain a decent performance with the help of Ant Lion Optimization-assisted feature selection.

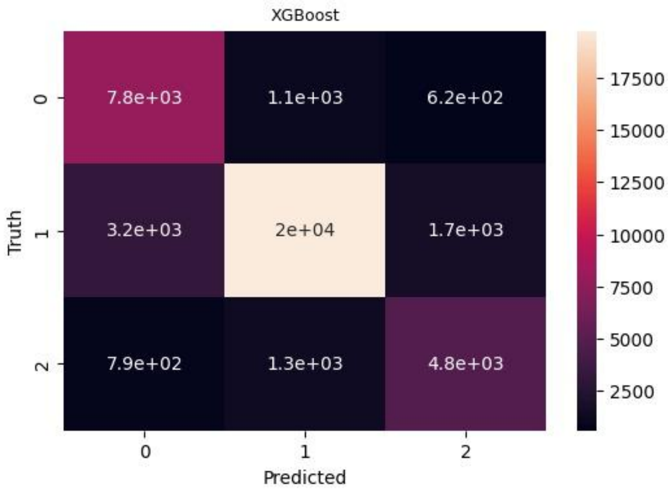

Figure 13: Confusion Matrix of XGBoost Model for Stress Classification

Figure 13 shows how well XGBoost model's confusion matrix predicts stress levels across three categories, low (0), moderate (1), and high (2). While there are a few misclassifications in classes 0 and 2, XGBoost has great performance overall, with 20,000 accurate predictions in class 1 (moderate stress). There are 7,800 accurate predictions for class 0, 1,100 for class 1, and 620 for class 2 that were erroneously categorised. There is also considerable ambiguity in the Class 2 predictions: 4,800 were right, although 1,300 were wrongly labelled as Class 1 and 790 as Class 0.

Compared to DBN, XGBoost exhibits improved accuracy, particularly for high-stress class 2, although some errors still occur in differentiating between moderate and high stress (classes 1 and 2). These results suggest that the Ant Lion Optimization for feature selection effectively improves XGBoost's classification capability, leading to better performance, especially for the critical task of distinguishing higher stress levels.
These results demonstrate that DL and ML models' performance in stress categorisation is much enhanced when ALO is used for feature selection. The MLP model failed to achieve significant generalisation with recall scores below 90%, whereas the DBN model succeeded with scores over 95% in all four categories. The XGBoost model demonstrated exceptional performance in managing both low and high stress levels, but had difficulties in differentiating between categories of intermediate stress. After analysing the RMSE, MCC, and Kappa scores, XGBoost was determined to be the better model, with DBN following closely behind. Confusion matrices for DBN and XGBoost revealed areas where both models performed well, but also highlighted misclassifications, especially between similar stress levels. Overall, the ALO-enhanced feature selection process proves effective, offering promising results in stress classification and supporting the framework's applicability in real-world mental health monitoring solutions.

6. Conclusion and future works

This paper presents a tailored ALO model driven by DL utilising heart rate data to allow stress detection and categorisation. This model was created to solve the problems utilising another one by means of past approaches. Sometimes overfitting comes from RFE and PCA. One avoids overfits and the model might efficiently lower the data dimensionality. Using ALO in feature selection is doable and lets this happen. Stress categorisation problems affect DL models such DBN, MLP, and XGBoost. These designs help to raise the accuracy and flexibility of the model. Using thorough evaluation measures such as Cohen's Kappa, RMSE, and MCC will help one to get a more whole perspective of the model's performance. This is not the case with traditional measurements requiring accuracy and precision. Statistics show that the suggested method improves multi-class stress detection capacity. This offers a more dependable and adaptable response for actual application. This approach offers a means to considerably improve stress detecting systems and support more effective treatment of mental health issues.
It will look into future prospects to expand the technique to other diverse datasets and physiological markers outside merely heart rate. This paper talk about two situations of physiological signals: EEG and GSR. Let shall go over two instances of physiological signals: Together, these two are Furthermore, the real-time properties of the edge-based method might enable ongoing observation of the generated stress levels arising from regular activities. Considering the possibilities of including more sophisticated bio-inspired algorithms such as GA or PSO might help the model performance to increase even further. Other appealing methods include on particle swarm optimisation and genetic algorithms. This would enhance the model and simplify its use in more broad contexts, including the management of stress in the workplace or the awareness of mental health issues in medical institutions. Not least of all, if the range of multi-class categorisation included various cognitive and emotional states, the model would be stronger.

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