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Article

Comprehensive evaluation of humanistic qualities and mental health of computer science teachers based on biomechanical algorithms

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Abstract: In the field of computer science education, humanistic traits and mental wellness are crucial. However, the role of biomechanics, especially factors like gait and posture, is often overlooked. Biomechanically, proper gait and posture are essential for maintaining physical balance and distributing forces evenly across the body. This study combines DL and biomechanical methods to assess students. Importantly, it delves into how gait and posture, as biomechanical factors, link to educators' mental health. Gait anomalies can signal stress or fatigue. A hesitant or unsteady gait might disrupt teaching focus and flow, inducing anxiety. Poor posture, like prolonged slouching, leads to muscle strain and pain. This physical discomfort can spark negative emotions, reducing teaching enthusiasm and confidence. The questionnaire included 300 computer science professors (180 women and 120 men) from Chinese universities. Data were collected through psychological questionnaires assessing insomnia, mood, fatigue, and depression. Anthropological factors such as social interaction and communication skills. Wearable sensors have been used to collect biomechanical data, including reactions and activities. The proposed Kalman filter algorithm with a modified visual-geometry group (KFA+MVGG) method allows a comprehensive assessment of computer science students' psychological well-being, personality, and physical activity through activity and by accurately recording mental signals in real-time. Experimental studies show significant increases in classification accuracy and efficiency, outperforming previous benchmarking methods. The findings that sedentary behavior, poor posture, and restricted movement are linked to fatigue and poor mental health emphasize the importance of biomechanics. The KFA+MVGG offers valuable insights. By understanding these biomechanical impacts, teachers can be more aware of their body mechanics. This can potentially enhance their mental health and overall well-being, ultimately benefiting their teaching in the computer science realm.

Keywords: humanistic qualities; computer science teachers; biomechanical algorithm; gait and posture; mental health; Kalman filter algorithm with modified visual geometry group (KFA + MVGG)

1. Introduction

Teachers' participation in shaping the educational environment goes past simply passing on information, which includes creating a stimulating and supportive environment for students [1]. In computer science and engineering, in which rapid technological advances and enhancing pedagogical techniques are common, the importance of human traits and teachers' psychological understanding becomes extra apparent [2]. Personality developments consisting of empathy, compassion, and sturdy interpersonal abilities are crucial to constructing meaningful relationships among teachers and students. These features enable teachers to create inclusive classrooms that inspire collaboration, essential thinking, and creativity, all of which are essential to achieve an ever- changing technological environment [3]. However, the demands on computer science teachers are multifaceted, together with rigorous curriculum requirements, the need to stay on top of technological developments and the challenge of getting students to do it otherwise and engaging [4] the mental fitness of these instructors is dominant, affecting not only their well-being but also their students' learning [5]. Research has an increasing number of shown a link between a teacher's mental health and their ability to expose humanity, suggesting that properly-supported teachers are in a better role to inspire and inspire students [6]. Furthermore, the unique challenges faced by of computer science teachers, which include the pressure to combine practical skills with theoretical knowledge, frequently lead to stress and burnout [7]. These findings highlight the need for a greater knowledge of the interaction among positive personality traits and mental health inside this specific domain [8]. Examining those theories gives stakeholders in education with valuable insights into the complexity of teaching in a rapidly evolving discipline and encourages the importance of educators in promoting mental health and humanity [9]. As the educational landscape continues to evolve, it is important to prioritize the well-being of teachers, especially in technological fields such as computer science, to create an effective learning environment [10]. Recognizing the critical role that personality and mental health play in effective learning, it is important to develop strategies to support the next generation of educators in the important mission of empowering students [11]. The pharmacology team handled the psychological aspect of the situation by instructing the tiny machines to provide the appropriate medication to eliminate any psychic instability and guarantee a constant, stable temperament [12]. Without ignoring the revived requests to encourage automation and improve the quality of employment life, robotics presently looks for synergies that can optimize the environmental circularity of conventional robotic results while contributing high-quality inputs to more customized small-scale endeavors [13]. The intricate connection between instructors' mental health and personality features is essential to fostering a supportive learning environment, especially in disciplines like computer science where technology is always evolving and advancing quickly [14]. It is increasingly more crucial to attend to educators' well-being as their workload increases. Teachers who receive support have better personal health and are more equipped to provide a welcoming, creative, and cooperative learning environment [15]. By placing a higher priority on teachers' mental health, educational institutions can better prepare teachers to manage the demands of fusing theoretical knowledge with practical abilities, which will eventually result in improved teaching and learning results [16]. It emphasizes the value of all-encompassing support networks for teachers, recognizing that their health is essential to both the academic achievement of their pupils and the system as a whole [17].

The purpose of this research was to evaluate the mental health and demographic characteristics of computer science teachers, focusing on key determinants of fatigue and emotional exhaustion. The study used the Kalman filter algorithm with a modified visual geometry group (KFA + MVGG) model to assess the physical and mental health burnouts of teachers in Chinese universities.

KeyContributions

1) The KFA + MVGG model increased classification efficiency and accuracy in measuring mental health outcomes compared to traditional methods.
2) The novel method successfully combined biomechanical data with cognitive measures in real-time, providing teachers with a comprehensive assessment of well-being.
3) The study showed a significant correlation between sedentary computer science teachers, poor posture, and deteriorating mental health.
4) The research findings provide educators with valuable information for designing targeted interventions aimed at promoting mental and physical well-being.

Organization of the study: Part 2 defines the related work, the methodology is recognized in Part3, the result is presented in Part 4, the discussion is shown in Part 5 and the conclusion is demonstrated in Section 6.

2. Related works

An educator's mental health possesses a substantial influence on both psychological wellness and academic success was proposed [18]. Factors such as hectic schedules, extracurricular pursuits, and unforeseen shifts can all cause stress, hurting instructors' resilience methods and students' mental health. The use of a principal's humanistic strategy for educational character-building initiatives in Malang, a city in Indonesia was investigated [19]. Findings indicated that personal achievement and inspirational individuals motivate this method, which considerably enhanced the execution of character development programs. The Polish teachers revealed the socio-demographic, related to health presented [20] a COVID-19-related variables all have a substantial impact on teacher anxiety, depression, and stress. Particularly susceptible categories included young women who worked in large towns or taught remotely. Additionally, it emphasized the need for long-term preventative initiatives and sustained assistance systems. The relationship between burnout among teachers and students' evaluations of teacher social and emotional competence (SEC) was explained [21]. The findings revealed that greater levels of teacher burnout predicted deeper SEC evaluations, underlining the relationship between instructor and student opinions. Work-related stress is an increasing problem in modern society, especially for teachers. The origins, disagreements, and physical manifestations of stress in Cuban educators, highlighting the significance of self-care in maintaining a good work environment was investigated [22]. To investigate how inbuilt characteristics such as mental agility and resilient personality traits affect the mental health of school instructors in India's Haryana state was determined [23]. Persistence proved to be a major mediator in the study, whereas independence was contradictory. Female instructors had more mental toughness and perseverance. The practical effects have increased persistence, decreased stress, and leadership development. The humanist strategy of education concentrates on its goals, courses, and ethical consciousness was explained [24]. It examined personal inheritances, religious instruction, religious schools, and parental authority. The study employed empirical analysis to give useful information on education and mental health. During the COVID-19 epidemic, educators' mental health suffered dramatically was established [25], with greater levels of anxiety and distress for both personally and distant educators. It showed the pandemic's instructional influence on educators' mental health.

The educators' mental health differs by work position, with thriving educators having fewer instances of depression and fatigue, while individuals with average mental health had better work satisfaction and effectiveness viewpoints was evaluated [26]. The connection between educator wellness and student psychological wellness, as well as whether characteristics such as instructor attendance and absences reduce the correlation was examined [27]. Revealed that stronger educator health was connected with higher academic achievement and reduced emotional distress, whereas higher instructor depressed symptoms were linked to reduced well-being. Examined how constructive psychology affects teacher applicants' pleasure and feelings of depression in a Hispanic Educational University. The optimism and psychological fortitude were the major determinants of pleasure and signs of depression were revealed [28]. The educators and mental health assistants who implemented the Jesse Lewis Choosing Love program in a different educational context was presented [29]. It employed open-ended questions and interviews to further comprehend the specific requirements of pupils in this context. Five common themes have been discovered: shifts between staff and students, teamwork, an understanding of student requirements, and current security. The results have implications regarding potential educational curricula and provide recommendations for SEL deployment. The findings provided [30] a semi-randomized assessment of the fostering mental health in school (PROMEHS) system, created by a European group supported through the EU and including over 10,000 students from six different nations, to determine its efficacy in improving social and emotional development, resiliency, and schoolwork. The issues and modifications in the South African educational institution can have an impact on educators' occupational mental health, causing enrollment rates to shift. The management of school administrators has a direct impact on teachers' occupational welfare. The link between principal management actions and educators' occupational well-being, with an emphasis on two types of leadership. The beneficial work-related emotional contentment can lead to higher retention of educators through improved professional engagement was discovered [31].

Occupational health and safety (OHS) regulations could handle employee security mostly autonomously from robotic behavior until both creatures operated in energetic, although distinct, situations was presented [32]. Using information from his tracking gadgets, an AI bot recommended the minimal amount of training required to keep him at his current level of fitness.

Nowadays sports sector is struggling with degrading trends. Athletics as they understand it is evolving due to new technology, which is drastically changing what it means to be a participant according to the author of [33]. These trends necessitate fresh perspectives on athletics that take into account its human components. For computers to be adopted and used in a range of contexts, it is essential to guarantee the security of human controllers during human-robotic encounters.

The mental health, physical activity, and biomechanical factors of undergraduate students were examined [34]. The findings indicated that elevated levels of depression, stress, and anxiety were linked to inadequate biomechanical positions, including forward head position and asymmetrical movement. Cognitive resilience and levels of physical exercise were also assessed.

The theoretical and practical approaches created for the investigation of human motion are covered in that research [35], along with the background and method of human action biomechanics. The combination of modern scientific methods and the continual creation of new technologies were proposed to be beneficial for future research on the biomechanics of human activity and its therapeutic applications.

Based on movement efficiency, that work [36] provided a functional relationship between biomechanical and neurophysiological aspects about controlling posture in both standing and walking. Evidence pertaining to the neurophysiological and biomechanical processes was examined, along with the impact of proprioceptive data on movement and posture regulation.

A consistent basis for reductions in cervical sense of balance, performance-oriented balance, and limits of stability (LOS) in people with forward head posture (FHP) was identified [37]. Heterogeneity and a dearth of high-caliber research, however, undermined the body of Knowledge. There was inconclusive evidence about the association between FHP and positional stabilization and stable balance, and limited evidence connected FHP to vestibular deficiencies and gait issues.

3. Methodology

This section critically examines and classifies teachers' mental health indicators. Data collection involved the collection of relevant mental health measures and associated measures. The pre-processing was performed with Min-Max normalization to ensure consistency of the data and improve the performance of analyses. PCA was used for feature extraction, which reduced dimensionality while retaining important information for easy classification of mental illness. The study used a novel method that includes KFA and a visual geometry group modified together using the MVGG model. The hybrid approach utilizes the strengths of KFA+MVGG, optimizing the classification system for increasing the accuracy and reliability of mental health assessment among teachers.

3.1. Data collection

The study utilized primary data collected from 300 computer science teachers (180 women and 120 men) across various universities in China. The data-gathering procedure was complex and systematic, including both quantitative and qualitative methodologies. Psychological questionnaires, personality tests, and wearable sensors that track posture and activity were used to gather data, giving a thorough understanding of the connection between personality qualities and mental health. Participants completed a series of psychological questionnaires designed to assess key dimensions of mental health, including fatigue, depression, sleeplessness, and emotional sensitivity. Furthermore, personality traits such as communication skills and social interaction were assessed through standardized data sets. In addition to intellectual data, mobile sensors were used to collect biomechanical information, with an emphasis on tracking posture and daily movements. Teachers gained important insights into the intricate connection between personality characteristics and mental health because of this multifaceted approach. Investigators could evaluate the relationship between posture and joint movement and cognitive and psychological state by examining the biomechanical components of these physical characteristics. A greater awareness of one's actions is made possible by the combination of biomechanical data and cognitive tests, which eventually helps educators create environments that are supportive of learners' mental wellness and development as adults.

3.2. Pre-processing using min-max normalization

Wearable sensors use Min-Max normalization to measure the raw biomechanical data collected, ensuring that all factors are within standard ranges, typically [0, 1]. This method helps to remove the influence of different units and scales obtained between different measurements, such as stance angles and movement speed, allowing unbiased comparisons and better incorporation into psychological questionnaire scores. The minimum and maximum values from the dataset for each biomechanical feature are determined using Equation (1):

$$x' = \frac{x - min(X)}{max(X) - min(X)} \tag{1}$$

where $x'$is the average value, x is the initial measurement, $min(X)$ is the lowest level in the feature and $max(X)$ is the highest level of the feature.

Change all attributes: Apply the equation to each attribute in the dataset, resulting in a regularized data set with all values ranging from 0 to 1. These preliminary steps ultimately contribute to a comprehensive study of computer science teachers' mental health and personality traits.

3.3. Feature extraction using principal component analysis (PCA)

The basic idea of PCA is to linearly transform the biomechanical data collected by computer science teachers into a low-dimensional subspace to maximize the variability of the dataset. The resulting vectors are an uncorrelated vertical basis set, and the relationship between movements is clearly understood as examples and consequences of mental health. The principal elements are right-angled because they correspond to their vectors in a symmetric covariance matrix. In the context of this study, consider K observation from the biomechanical data collected from the participants, each represented in an n-dimensional space. The subsequent steps outline the PCA computation: Calculate the mean vector: compute the mean vector u of the observations using Equation (2):

$$\mu = \frac{1}{l}\sum_{j=1}^{l} w_j \tag{2}$$

Compute the covariance matrix: Estimate the covariance matrix S for the observed biomechanical data using Equation (3):

$$T = \frac{1}{l}\sum_{j=1}^{l}\left(w_j - \mu\right)\left(w_j - \mu\right)^S \tag{3}$$

Calculate Eigenvalues and Eigenvectors: Determine the eigenvalues and their corresponding eigenvectors of the covariance matrix$S$, where$\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_l \geq 0$.

Principal component calculation: From the original l variables, calculate the principal components using the below Equations (4)–(6).

$$z_1 = b_{11}w_1 + b_{12}w_2 + \cdots + b_{1l}w_l \tag{4}$$

$$z_2 = b_{21}w_1 + b_{22}w_2 + \cdots + b_{2l}w_l \tag{5}$$

$$z_x = b_{l1}w_1 + b_{l2}w_2 + \cdots + b_{ll}w_l \tag{6}$$

λ_lValues are uncorrelated (orthogonal). The initial key elementλ_1 represents the majority of the variation in the information set, followed byλ_2, which describes the balance of maximal variation. In practical application, a few larger eigenvalues typically dominate the others. To ensure effective dimensionality reduction, it is common to retain the extracted PCA explain at least 80% of the total variation in the dataset. This threshold ensures that the PCA retains the most significant features relevant to understanding the mental health and humanistic qualities of computer science teachers about their biomechanical data.

3.4. Mental health classification using kalman filter algorithm with modified visual geometry group (KFA+MVGG)

Modified Visual Geometry Group (MVGG): The system has thirteen Conv1D layers, five maximum pooling levels, two batch normalizing levels, and three layers that are completely linked. The VGG structure consists of 2-D layers of convolution with filtering depth and dimensions identical to arrangement A, ideal for classification applications. The suggested MVGG varies from VGG in terms of filter count, receptive field dimensions, and activation mechanism. The suggested design simplifies memory requirements by reducing variables. The update from VGG includes batch normalization of layers and hyperparameter tuning for the fully interconnected layer drop-outs. This structure is intended to categorize movement patterns and psychological indicators related to teachers' psychological wellness and humanistic traits.

The activating function is crucial in DL because it adds irregularities to the system and improves training method efficiency. The formations $A, B, C, D, E,$ and F use the Rectified Linear Unit (ReLU) activation mechanism. Simulations with activation features, including ReLU, Exponential Linear Unit (ELU), and Leaky ReLU, show that the ELU outperforms the other two options. The suggested MVGG model uses the ELU activate function. This study uses the KFA algorithm method with a basic learning speed decay strategy across all setups. Equation (7) indicates that the learning efficiency decreases by 0.1 per 300 epochs.

$$\eta = \eta 0 \times 0.1^{\frac{M}{300}} \tag{7}$$

The start rate for learning $\eta 0$ is set at0.01. The number of batches is set to 128 for changeable width and depth settings $(A, B, C, D, E, \text{and} F)$ and 64 with MVGG. **Figure 1** shows the architecture of MVGG.

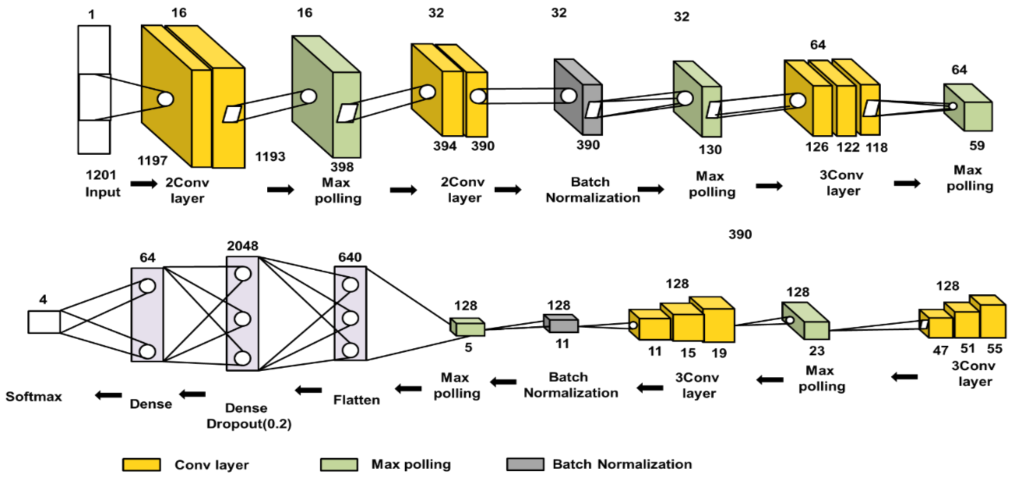

Figure 1. Architecture of MVGG.

To prevent overfitting with training information, early halting is implemented. Training ends if the accuracy of validation fails to improve considerably after 30 epochs. The system undergoes training only over 200 epochs. To enhance the generalization capacity of MVGG compared with previous setups. To prevent over-fitting, KFA is used in the subsequent completely linked layer. Weight vectors are impacted by an amount of 0.001.

Kalman Filter Algorithm (KFA): Kalman's filter (KF) represents minimalist methods that use prior state knowledge rather than complete historical inputs to create an informed forecast about the method's present condition. Kalman gains l constitutes one of the more crucial design factors for the KF since it accomplishes all of the enchantment. The KFA adjusts the amount of l based on the scenario to manage the percentages assigned to the technique's anticipated condition or wearable sensor data. **Figure 2** depicts the mechanisms of the KFA.

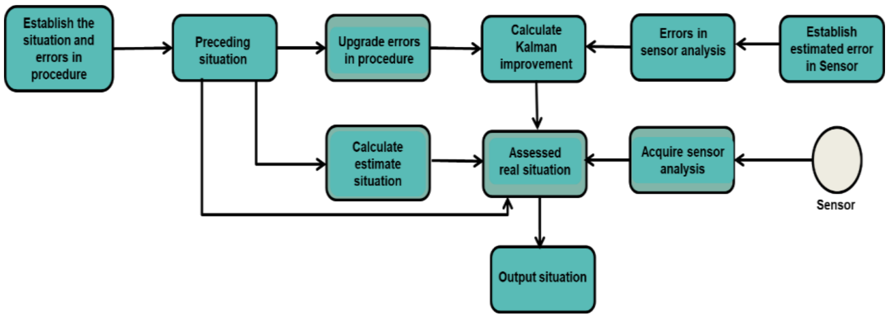

Figure 2. Mechanisms of the KFA.

Each location has its own set of noise elements and can have a significant impact on the sensor readings. In this study, an evaluation of computer science teachers' mental health, humanistic qualities, and physical activity was investigated using biomechanical data sensor measurement with interference and suppose S_s is at moment$s$. The KFA uses a process diagram to anticipate the system's state and compares it with present sensor inputs to determine the expected (S_{s-1}) at times $s-1$. Next, the step-by-step operation of the KFA, namely how it eliminates disturbance from sensor data, was quickly discussed. In the initial stage, the assumed mental health is calculated based on the previously established value through the following Equation (8).

$$S_o = B \times S_{s-1} + A \times v_s \tag{8}$$

B And A reflects the states of transitions and regulation matrices, whereas S_o represents the subjectively predicted distress. The previously established conditions at moment $s-1$ are denoted by S_{s-1}, whereas ut denotes the control variable. Uncertainty regarding the internal predicted conditions is given by the covariance aspect, which is modified by Equation (9).

$$O_{predicted} = B \times O_{s-1} \times B^S + R \tag{9}$$

In Equation (9), B and B^S indicate the condition transitions vector and its translation, respectively. The initial value for correlation is O_{s-1}, and the expected error in the procedure is denoted by R. After creating an internal estimation of the technique's next stage and adjusting covariance, Kalman's contribution L is modified as shown in Equation (10).

$$L = \frac{O_{predicted} \times G^S}{G \times O_{predicted} \times G^S + Q} \tag{10}$$

G And G^S indicates the data vector and transposition, respectively, while Q representing the expected error in measuring. Assuming the present value from a temperature sensor at the time t appears as zt. The anticipated condition utilizing KF is subsequently estimated by Equation (11).

$$S_s = O_{predicted} + L(y_s - G \times O_{predicted} \tag{11}$$

The subsequent phase is to alter the difference parameter for the following iteration, as seen in Equation (12):

$$o_s = (J - L \times G) O_{predicted} \tag{12}$$

A hybrid approach to mental health classification, MVGG, and KFA, exploits their strengths for increased predictive accuracy. The MVGG model includes 13 Conv1D levels, 5 MaxPooling levels, and 2 batch normalization levels, which correspond to the movement patterns that are classified and their effect on the mental symptoms experienced by teachers with this mental illness. It utilizes ELU and ReLU, exhibiting higher performance compared to other methods consisting of Leaky ReLU. This model additionally incorporates dropout layers and L2 regularization to lessen overfitting. Conversely, KFA deals correctly with sensor data by way of describing the current state based totally on past observations, allowing for actual-time adjustments that successively serve to predict psychological symptoms, resolve uncertainties, and iteratively refine predictions. Combining KFA-MVGG capabilities with advanced filtering techniques to ensure improved classification performance, enhancing the reliability of all mental health assessments in educational settings. Thus, this method greatly advances the expertise of the factors affecting teachers' psychological well-being through the evaluation of biomechanical data. The KFA-MVGG Pseudocode is presented in Algorithm 1.

Algorithm 1 Pseudocode of KFA-MVGG

1. Initialize parameters:

Learning rate$\eta 0 = 0.01$, decay factor = 0.1, batch size = 128

Set dropout rate = 0.2, L2_regularization = 0.001

Initialize MVGG layers (Conv1D, MaxPooling, BatchNorm, FullyConnected)

2. For each epoch in range (300):

a. Update learning rateηusing decay: $\eta = \eta 0 * 0.1^{\frac{M}{300}}$

b. Load data in batches of size batch size

c. For every batch:

i. Execute advancing pass over MVGG with ELU activation

ii. Calculate loss using cross-entropy

3. Implement early stopping:

If validation accuracy does not improve for 30 epochs:

Break training loop

4. For each time step s:

a. Predict previous state: $S_o = B \cdot S_{s-1} + A \cdot v_s$

b. Predict uncertainty: $O_{predicted} = B \cdot O_{s-1} \cdot B^S + R$

c. Compute Kalman gain: $L = \frac{O_{predicted}}{G \cdot O_{predicted} \cdot G^S + Q}$

d. Update state estimation: $S_s = O_{predicted} + L(y_s - G \cdot O_{predicted}$

e. Update uncertainty: $o_s = (J - L \cdot G)O_{predicted}$

5. Output:

Trained model parameters and state estimations for mental health classification

4. Performance analysis

The Python framework was used in conjunction with a Windows 13 operating system that was powered by an Intel® Core i9 CPU and equipped with 16.00 GB of RAM. The comprehensive evaluation of humanistic qualities and mental health of computer science teachers, based on biomechanical algorithms, has yielded three findings that highlight key predictors of teachers' well-being, depression, and anxiety. It summarizes the importance of various variables that influence educators' mental well-being and physical wellness expressed through the mean decrease in accuracy, which indicates the contribution of each predictor to the classification model's accuracy.

4.1. Teachers' positive well-being

Table 1 and **Figure 3** evaluate teachers' positive well-being and identify family support as the most significant predictor, with a high mean decrease in accuracy of 47.19%. This underscores the role of family as a cornerstone for mental and emotional well-being. Following closely, stress (40.84%) and sedentary behavior (35.12%) also emerge as critical factors, highlighting the adverse effects of stress and inactivity on well-being. The proposed KFA+MVGG method effectively analyzes these predictors by categorizing movement patterns and psychological indicators linked to teachers' well-being. Autonomy support (33.56%), work-life balance (31.78%), and poor posture (29.87%) reflect the significance of teachers' professional autonomy, balance between work and personal life, and ergonomic factors on their overall health. Lesser yet important influences include physical activity (28.45%), communication skills (26.41%), and emotional resilience (22.30%). Finally, age (19.22%), depression (9.43%), and anxiety (4.11%) have a relatively lower impact on predicting positive well-being but indeed play a role.

Table 1. Predictors of teachers' positive well-being.

Predictors	Mean Decrease in Accuracy (%)
Family support	47.19
Stress	40.84
Sedentary Behavior	35.12
Autonomy support	33.56
Work-Life Balance	31.78
Poor Posture	29.87
Physical Activity Level	28.45
Communication Skills	26.41
Emotional Resilience	22.30
Age	19.22
Depression	9.43
Anxiety	4.11

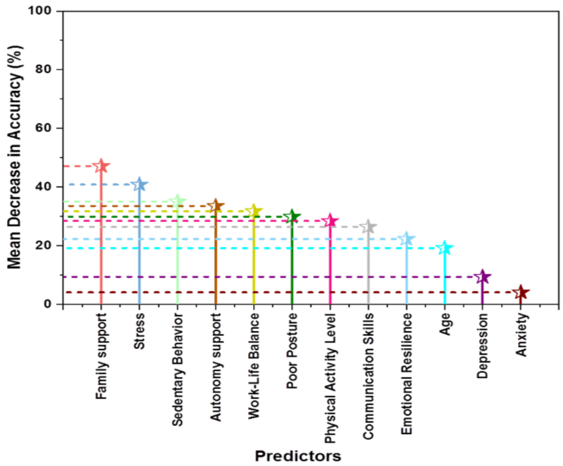

Figure 3. Teachers' positive well-being outcomes.

4.2. Teachers' depression state

In **Table 2** and **Figure 4**, predicting the teacher's depression, anxiety stands out as the most significant factor, with a substantial mean decrease in accuracy of 89.58%, indicating its close relationship with depression. Other major factors include emotional well-being (25.27%) and stress (24.61%), showing that teachers' emotional stability and stress levels are key contributors to depressive states. The proposed KFA+MVGG method effectively categorizes these predictors, analyzing their influence on mental health outcomes. Psychological well-being (19.85%) and age (14.01%) also play meaningful roles, while family support (11.99%) offers moderate predictive value, pointing to the role of familial relationships in mitigating depression. Lower but notable contributors include work-life balance (22.70%), physical activity level (21.15%), emotional resilience (17.85%), sedentary behavior (19.22%), and poor posture (16.35%), and communication skills (13.78%), all of which illustrate the complex web of mental health influencers.

Table 2. Predictors of teachers' depression state.

Predictors	Mean Decrease in Accuracy (%)
Anxiety	89.58
Emotional well-being	25.27
Stress	24.61
Psychological well-being	19.85
Age	14.01
Family support	11.99
Work-Life Balance	22.70
Physical Activity Level	21.15
Emotional Resilience	17.85
Sedentary Behavior	19.22
Poor Posture	16.35
Communication Skills	13.78

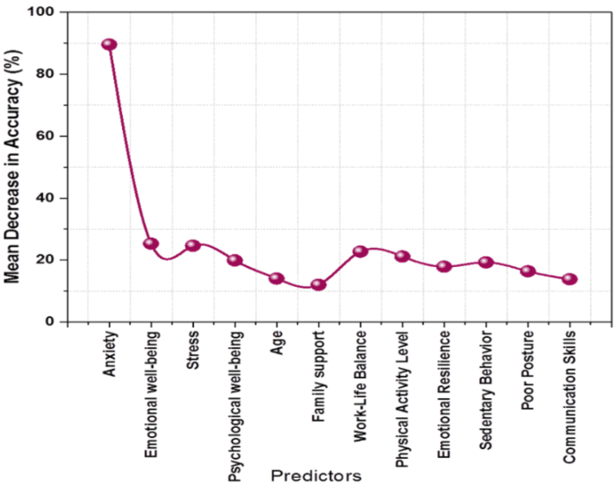

Figure 4. Teachers' depression state results.

4.3. Teachers anxiety score

In the case of anxiety, depression emerges as the most critical predictor, with a mean decrease in accuracy of 89.10%, indicating the strong interconnection between anxiety and depression presented in **Table 3** and **Figure 5**. The proposed KFA+MVGG method effectively categorizes these predictors, revealing other notable factors including stress (23.65%) and psychological well-being (19.19%), showing that psychological health and stress management are vital in controlling anxiety levels. Emotional well-being (17.17%) and sedentary behavior (18.91%) further highlight the psychological and physical aspects influencing anxiety. Predictors like work-life balance (20.22%), emotional resilience (15.50%), and physical activity level (17.03%)

also play crucial roles. Additionally, poor posture (13.29%), communication skills (11.88%), age (8.06%), and family support (5.19%) have smaller but yet significant impacts on anxiety scores.

Table 3. Predictors of teachers' anxiety score.

Predictors	Mean Decrease in Accuracy (%)
Depression	89.10
Stress	23.65
Emotional well-being	17.17
Psychological well-being	19.19
Sedentary Behavior	18.91
Emotional Resilience	15.50
Work-Life Balance	20.22
Physical Activity Level	17.03
Poor Posture	13.29
Communication Skills	11.88
Age	8.06
Family support	5.19

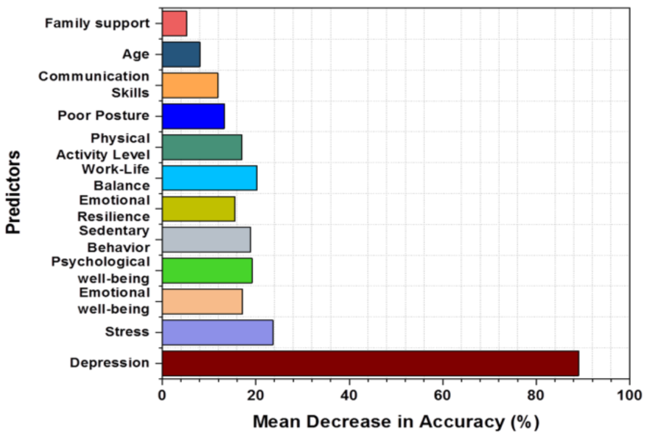

Figure 5. Predictors of teachers' anxiety score.

4.4. Comparative analysis with existing methodologies

In this comparison phase, the proposed method KFA + MVGG with cost-sensitive algorithms is evaluated to assess its effectiveness in predicting burnout among educators. The focus is on understanding the performance of the model relative to established machine learning (ML) algorithms, including Decision Trees (DT), Random Forests (RF), and Support Vector Machines (SVMs) [38]. which have been widely used in prognostic studies for mental health research. Cost-sensitive is a technique that modifies the algorithm to evaluate the cost of misclassification related to classes. This method is mainly useful in the setting of burnout coverage because it emphasizes the importance of accurately identifying individuals at high risk of burnout to enable targeted interventions that can better meet the needs of at-risk teachers. Cost-effective methods aim to reduce the overall cost of misclassification, making them relevant for sensitive applications such as mental health prediction. **Table 4** and **Figure 6** provide the numerical and graphical representations of comparisons of teacher burnout predictions.

Table 4. Comparison of algorithms for teacher burnout prediction.

Algorithm	Balanced Accuracy	AUC	Sensitivity	Specificity
Cost-sensitive values				
DT [38]	0.768	0.822	0.766	0.769
RF [38]	0.817	0.904	0.871	0.763
SVM [38]	0.768	0.870	0.678	0.858
KFA+MVGG [Proposed]	0.830	0.910	0.895	0.700

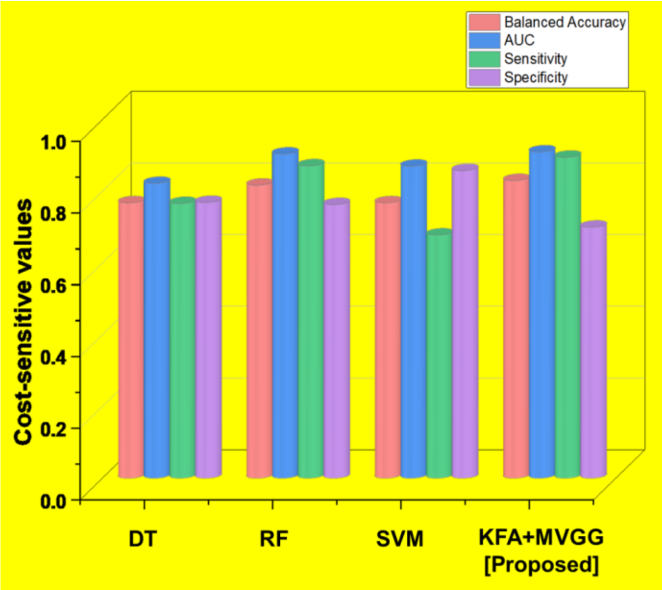

Figure 6. Comparison of algorithms for teacher's burnout prediction.

4.4.1. Balanced accuracy

Balanced accuracy provides a statistic for identifying positive as well as negative categories in task classification, which is particularly beneficial when the categories are not matched. It is derived as an average of sensitivity (True Positive Rate) and specificity (True Negative Rate) Equation (13).

$$\text{Balanced Accuracy} = \frac{\text{Sensitivity} + \text{Specificity}}{2} \tag{13}$$

The DT obtained a balanced accuracy of 0.768, which represents its moderate performance in identifying two classes. RF improved this performance, achieving a balanced accuracy of 0.817, indicating an increased ability to generalize between models. SVM exhibited a balanced accuracy of 0.768, which is similar to DT 0.768, indicating their relative proficiency in this case. In contrast, the proposed KFA+MVGG method achieved a balanced accuracy of 0.830, which outperformed all other algorithms. These improvements suggest that the KFA+MVGG is better at maintaining performance in both groups, resulting in a more reliable classification of mental health conditions among teachers.

4.4.2. Area under the curve (AUC)

It significantly generated the ROC curve; this value represents its capacity to differentiate across categories. An AUC value of 1 indicates perfect discrimination and a score of 0.5 implies no differentiation Equation (14).

$$\mathrm{AUC} = \sum_{i=1}^{\mathrm{n}-1} (\mathrm{TPRi} + 1 + \mathrm{TPRi}) \times (\mathrm{FPRi} + 1 - \mathrm{FPRi}) \tag{14}$$

The AUC of the DT algorithm was 0.822, demonstrating that it can distinguish well among both positive and negative categories, but there is room for improvement; the RF algorithm exhibited a higher AUC of 0.904, indicating its ability to discriminate learning between types compared to DT and SVM. SVM achieved an AUC of 0.870, indicating a reasonable performance but rather lagging behind RF. The proposed KFA+MVGG model achieved the highest AUC at 0.910, indicating good discriminatory power. These findings illustrate the KFA+MVGG method's ability to effectively categorize psychological disorders and recognize instructors at risk of mental illness.

4.4.3. Sensitivity

Sensitivity represents the percentage of positives properly detected by the algorithm. The elevated sensitivity suggests that the algorithm is good at finding affirmative instances Equation (15).

$$\mathrm{Sensitivity} = \frac{\mathrm{True\ Positives}}{\mathrm{True\ postivies} + \mathrm{false\ negatives}} \tag{15}$$

The DT algorithm recorded a sensitivity of 0.766, indicating a moderate ability to detect true positives. The RF model showed a significant improvement, with a sensitivity of 0.871, which proved its strong performance in capturing high-quality information. In contrast, SVM performed poorly with a sensitivity of 0.678, indicating a high risk of false positives. The proposed KFA+MVGG method achieved an impressive sensitivity of 0.895, indicating its ability to accurately identify teachers experiencing mental health problems. This high sensitivity reinforces the importance of the KFA+MVGG approach in educational settings, where timely identification of at-risk individuals is critical for intervention and support.

4.4.4. Specificity

Specificity determines the fraction of real biases successfully recognized by the model. This is significant for research where the algorithm proves successful in minimizing misleading results Equation (16).

$$\mathrm{Specificity} = \frac{\mathrm{True\ Negatives}}{\mathrm{True\ negatives} + \mathrm{false\ positives}} \tag{16}$$

The DT algorithm obtained a specificity of 0.769, indicating a reasonable ability to identify true negative cases; the RF algorithm showed a slight decrease in specificity at 0.763, indicating that while it excels in detection, it may have a slightly higher rate of false positives. In contrast, the SVM demonstrated 0.858 effectiveness in accurately detecting negative cases. However, the proposed KFA+MVGG method exhibited a specificity of 0.700, which, although lower than other algorithms, emphasizes the model’s focus on balancing increased sensitivity. Overall, the KFA+MVGG provides a promising balance in a psychological classification setting, addressing the need for accurate diagnosis and early intervention.

5. Discussion

A positive indicator of teacher well-being reveals a significant effect of family support, which affects significant mental health with an average decrease in accuracy of 47.19%. Anxiety and social behavior increased, with an average decrease of 40.84% and 35.12%, respectively, indicating a negative impact on the need for independence in activities and personality on their well-being in life, including participation. Conversely, anxiety emerges as the strongest predictor of depression, with accuracy decreasing by 89.58%, highlighting their strong relationship. Emotional well-being and stress further predict depression, whereas age and family support have lower effects. The interactions of these factors highlight the complex nature of mental health affecting teachers. The DT method is basic and interpretable, but it suffers from overfitting, particularly for large datasets, which results in poor generalization and its tendency to overfit the training data can cause a loss of accuracy when operating on unseen data. The RF algorithm, although it reduces overfitting through ensemble learning, can struggle with class imbalances. This means that subgroups may not be adequately identified, leading to poor sensitivity in critical applications such as psychological assessment. The SVM allows robust classification performance, especially at high altitudes. However, its effectiveness may decrease in the presence of noisy or overlapping clusters, often leading to high false-negative rates, which are particularly detrimental in psychological diagnosis. The proposed KFA+MVGG algorithm addresses this limitation by increasing the overall classification performance. With a balanced accuracy of 0.830, it avoids overfitting by using dropout layers and batch normalization. Its 0.910 AUC exhibits higher discriminatory power than RF and SVM. Additionally, the dynamic KFA transformation improves the sensitivity of the model by 0.895 and improves the specificity by 0.700, ensuring better identification of the best cases. This makes KFA+MVGG a more reliable solution for early identifying and participating in mental health screening. Because of its successful integration of biomechanical processes with cutting-edge neural networks, the proposed KFA+MVGG model outperforms more conventional models such as DT, RF, and SVM for assessing the humanistic traits and psychological wellness of science instructors. This combined method improves the accuracy of identifying complex relationships in multidimensional data about psychological and physical characteristics, enabling a more thorough evaluation. The KFA+MVGG model offers significant insights into the connection between position, mental health, and humanistic traits by using MVGG for extracting features and KFA for simplifying the model. This makes it a more useful tool for assisting teachers’ professional growth.

6. Conclusion

This study examined the mental health and humanistic characteristics of computer science teachers, focusing on determinants of burnout and emotional exhaustion. The study combining DL and biomechanical algorithms examined internal relationships coupled with the complexity between physical symptoms and mental health outcomes in teachers. Results indicated that family support, stress levels, and sedentary behaviors were significant predictors of teacher well-being, and anxiety and depression emerged as significant factors affecting mental health. The KFA+MVGG model performed better than traditional machine learning methods, resulting in higher classification and accuracy in predicting burnout among subjects. In particular, KFA+ MVGG exhibited a balanced accuracy of 0.830, an AUC of 0.910, a specificity of 0.895, and a high sensitivity of 0.700, which highlighted its effectiveness in identifying teachers at risk of burnout. One disadvantage of this research is the absence of longitudinal data, which can present more insights into the fluctuating patterns of mental health within educators. In addition, the use of cross-sectional designs reduces the capacity to show causation between predictors and mental health outcomes. Future research could examine the long-term effects of targeted interventions based on the DL model, assessing changes in teachers' mental health and demographic characteristics over time. Furthermore, expanding the study to include more diverse populations of teachers in different disciplines and industries would enhance understanding of the complex factors affecting teachers' psychological well-being.

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