Smart Wearable Devices for Monitoring Cognitive and Behavioural Disorders in Students

Shilpa S. Ruikar[1], Mehul Manu[2], Nupur Giri[3], Chandrashekhar Ramesh Ramtirthkar[4], Priya Gupta[5], Ogabek Solayev[6], Shital Sachin Kare[7]

[1](Corresponding Author), Krishna Institute of Science and Technology,
Krishna Vishwa Vidyapeeth "Deemed to be University",
Taluka-Karad, Dist-Satara, Pin-415 539, Maharashtra, India
shilpa_ruikar@yahoo.co.in

[2]School of Allied Sciences, Graphic Era Hill University Bhimtal Campus;
Centre for Promotion of Research, Graphic Era (Deemed to be) University
Dehradun, Uttarakhand–248002, India
mmanugehub@gmail.com

[3]Department of Computer Engineering, Vivekanand Education Society's Institute of Technology (VESIT), Mumbai
nupur.giri@ves.ac.in

[4]Associate Professor, Department of Mechanical Engineering, Vishwakarma Institute of Technology, Pune, Maharashtra, 411037
email ID :chandrashekhar.ramtirthkar@vit.edu

[5]School of Sciences,Noida International University,Uttar Pradesh 203201,India. priya.gupta@niu.edu.in

[6]Department of Pedagogy and psychology, Urgench state university, Urgench Uzbekistan,
ogabek.s@urdu.uz
0009-0009-4203-5467

[7]Assistant Professor, Commerce Management and Computer Science(CMCS) College, Nashik.
shinde.sheetal6aug@gmail.com

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ABSTRACT:
The rising rate of the cognitive and behavioural disorders amongst the students has necessitated the emergence of sophisticated monitoring systems that would help in detecting the disorders early and taking appropriate measures. The suggested architecture will be based on a multi-layered scheme where the data acquisition, communication, and data processing layers, and the application layer will be engaged. It does this by using data preprocessing and feature extraction algorithms to improve quality of data and machine learning (ML) and deep learning (DL) algorithms like Support Vector Machines (SVM), Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks to classify and predict cognitive states. The results of the experiments indicate that deep learning models, particularly, the hybrid CNN-LSTM models are better in recognising stress, anxiety, and behavioural abnormalities compared to the traditional methods. Irrespective of the

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challenges in terms of data privacy, practicality of the appliances and generalization of the model, the proposed framework will provide a viable and scalable solution to track the mental condition of the students. The research can be used in the creation of intelligent healthcare and educational technologies, since it offers an in-depth, AI-based wearable monitoring system, which is student-specific. The provided plan can result in improved diagnostic outcomes, improved grades, and the health of students in general.

Keywords: Smart Wearable Devices, Cognitive Disorders, Behavioural Monitoring, Machine Learning, Deep Learning, Student Mental Health, IoT, Real-Time Monitoring.

I. Introduction

The problem of cognitive and behavioural disorders in students has become a hot issue in the contemporary educational and health care systems. Various disorders like attention deficit hyperactivity disorder (ADHD), anxiety, depression, and other disorders related to learning greatly influence the performance of students in school, their emotional stability and social development. These disorders should be detected early and monitored to ensure that the disorders are treated in time and that their outcomes are better in the long run. Nevertheless, the conventional diagnostic methods, based on regular clinical check-ups and non-quantitative analysis, can hardly reflect dynamic changes in cognitive and emotional conditions. This drawback requires the creation of uninterrupted, objective, and technology-based monitoring solutions. Herein, the wearable technology has turned out to be an effective solution in real-time health monitoring. Physiological parameters that can be monitored constantly by wearable devices with advanced biosensors include heart rate variability (HRV), electrodermal activity (EDA), motion patterns, and sleep behavior. Such devices allow monitoring to be done in the natural setting like classrooms and homes without any intrusion, and this makes them especially apt with student populations. The accelerated development of wearable technology and its adoption in the healthcare system have been extensively reported, and it is claimed that it can be used to monitor continuously and personally (Ometov et al., 2021). Moreover, wearables available to consumers have shown to be effective in stress, sleep, and biofeedback tracking, thus strengthening their usability in the real-life environment (Peake et al., 2018).

The use of wearable devices to detect stress which is an important sign of cognitive and behavioural disorders has gained a growing body of research. Constant monitoring of stress with wearable sensors has already delivered some good outcomes in a real-life setting, which proves that it is possible to record physiological reactions that are linked to mental pressure (Can et al., 2019). In the same way, machine learning-related methods utilized on biosignals have been effectively utilized in the detection of stress in regulated settings like virtual reality systems (Cho et al., 2017). These articles underscore the opportunity of wearable devices to deliver continuous and objective measurements, which can help identify possible mental health problems early. Besides stress detection, wearable devices have been employed more in tracking anxiety and other disorders. Anxiety can be manifested physiologically, such as heart rate and skin conductance variations, which are easily measurable with wearable sensors. Elgendi and Menon (2019) highlighted the promise of wearable devices in the evaluation of anxiety disorders and at the same time highlighted critical issues of data variability, sensor accuracy, and ethical issues. The reliability of consumer wearable devices, including smartwatches, in monitoring physiological parameters is further supported by their validation

to measure physiological parameters in real-time. As an example, Hernando et al. (2018) have shown that wearable devices are capable of robustly measuring heart rate variability in relaxation and stress states, so they can be used to monitor mental health continuously.

Their abilities have also been boosted by the incorporation of wearable devices and mobile and smartphone-based monitoring systems. Digital phenotyping using smartphones enables the continuous monitoring of behavioral and psychological trends, which gives more in-depth information about mental health issues. Faurholt-Jepsen et al., (2020) showed that smartphone-based monitoring can be used effectively to monitor illness activity among patients with bipolar, which exemplifies the possibilities of integrating wearable and mobile technologies to conduct a full assessment of mental health. This integration has helped in creating smart monitoring systems that are capable of giving real time feedback and assisting in the creation of customized interventions. Nevertheless, even with these developments, there are a number of challenges to the implementation of wearable-based monitoring systems to students. The problems of data privacy, ethical aspects, and acceptance of the user have to be taken into consideration. The constant observation of sensitive health information casts doubts on confidentiality and security, especially when minors are involved.

The proposed research will develop a smart wearable-based technology to track cognitive and behavioural disorders among students. The system can gather real-time information with the help of wearable sensors and process physiological and behavioral patterns with the help of advanced machine learning algorithms. The suggested framework will enable the integration of wearable devices and smart analytics along with cloud-based solutions to provide a scalable, efficient, and easy to use solution to mental health monitoring of students. In summary, the use of smart wearable devices is offering a new paradigm of cognitive and behavioural disorders monitoring since it offers continuous, real-time, and objective data of physiological and behavioural parameters. Combining wearable technology with machine learning and mobile platforms can revolutionize the mental health monitoring and enable the ability to identify it at an early stage and design the unique way of intervention. The research will contribute to this dynamic area since it proposes a smart tracking system of wearable nature that will be committed to assisting students to be healthy and prosperous in their learning.

II. Existing technologies and recent advancements

The development of wearable technology has greatly changed the way of monitoring in the healthcare system as physiological and behavioral parameters can be tracked on a regular basis and in real-time. Wearable gadgets combined with sophisticated sensors and communication systems have been popularly applied in tracking some health related conditions such as cognitive and behavioural disorders. In the early reviews, the increased significance of wearable health monitoring systems in delivering non-invasive, continuous, and customized healthcare solutions was highlighted (Kher and Patel, 2021). These systems take advantage of the biosensors, wireless communication, and data analytics to enable remote health monitoring, hence minimizing reliance on the conventional clinical evaluation. Recent developments in sensor technologies have also enabled the wearable devices to increase their capabilities. Miniaturized and extremely sensitive sensors are nanoarchitectonics-based, which allows detecting physiological signals like heart rate, electrodermal activity, and neural responses (Ariga et al., 2019). These advancements have greatly enhanced the accuracy and trustworthiness of wearable systems, and they can be applicable in the real-life setting to monitor mental illnesses. Moreover, wearables are also finding their way into the concept of precision medicine, where constant data gathering can be used to inform individual diagnosis and treatment plans (Babu et al., 2024). The use of wearable devices in continuous health monitoring and clinical has been studied in a large amount of literature. To provide an example, Karanjekar et al. (2025) have shown the suitability of wearable devices to continuously monitor vital

signs in the hospital environment in a randomized controlled trial. Their results included the capability of wearable devices to give an early warning about physiological anomalies, hence, enhancing patient outcomes. In a similar manner, digital self-tracking methods have been explored in the context of rehabilitation, where wearables allow tracking physical activity and recovery. Vogel et al. (2017) discussed the application of digital self-tracking to patients in cardiac rehabilitation and discovered that continuous monitoring increases patient engagement and facilitates recovery.

The wearable and mobile technologies have been instrumental in enhancing monitoring methods in the context of mental health. Monitoring systems based on smart phones have become a common area of research in regards to their capability of recording the behavioural pattern and offering information about mental health status. Bauer et al. (2020) carried out an extensive literature review regarding the use of smartphones as an application in the field of mental health, which shows the possibility of measuring mood, behavior, and cognitive patterns. Such systems can be used to monitor continuously even outside clinical contexts and provide a more in-depth picture of mental health status. Moreover, digital phenotyping as a concept has become an effective tool of measuring human behavior with the help of wearable and mobile devices data. Zhang et al. (2025) had authored on the clinical benefits of digital phenotyping, which is capable of detecting, diagnosing, and providing tailored treatment of mental disorders early. It has been coupled with artificial intelligence and machine learning through recent developments in wearable technology and has further augmented its application in cognitive and behavioural monitoring. Multimodal data generated by wearable devices amounts to gigabits and only the latest data analysis tools can help to make meaning out of it. Regularities of physiological signals could be analyzed with the help of the machine learning models and identified irregularities and predict potential disorders. This aspect is particularly useful when it comes to student populations, whereby, identifying cognitive and behavioural issues in a timely manner can be utilized to improve the academic performance and well-being to a tremendous scale. The wearable sensing, with smart analytics, enables the creation of proactive monitoring systems that can give real-time feedback and enable timely intervention. Regardless of such innovations, there are still a number of obstacles to adapting wearable-based monitoring systems. One of the major weaknesses is the variation in the physiological cues of different people that affect the predictive model validity and externalization. In addition, issues of sensor reliability, battery life and the devices usability must be addressed as well to ensure that the utilization of the gadgets becomes sustainable. The aspect of ethics, which encompasses questions of data privacy, data security and informed consent are particularly relevant in the case of tracking sensitive groups of individuals such as students. The endless data collection exposes the problem of misuse of personal data and strict data protection measures and code of conduct are needed.

Another important concern is that multimodal data of different sensors and devices are interwoven. The physiological, behavioural and contextual data require data fusion techniques and high computing capacity to integrate the data. In addition, there is no standardized data set and benchmarking systems that prevent the comparison of different approaches. In order to overcome these challenges, there is a need to collaborate interdisciplinary between the researchers, health workers and developers of the technologies. Altogether, the literature shows that wearable devices have a huge potential in the system of monitoring cognitive and behavioural disorders through real-time and constant analysis of the data. The new advances in sensors technologies, digital phenotyping, and intelligent analytics make it possible to develop a multifaceted monitoring system that can be used to enable early diagnosis and personal intervention. Nevertheless, issues of reliability of data and personalization, ethical issues and system integration are still important areas of focus over time. The existence of these loopholes underscores the need to have an elaborate and scalable wearable monitoring system that is specifically tailored towards the students which will form the focus of this study.

Table 1. Summary of Existing Technologies

Reference (APA Style)	Technique / Methodology	Key Findings	Limitations
Vijayan, V., Connolly, J. P., Condell, J., McKelvey, N., & Gardiner, P. (2021)	Review of wearable devices and data acquisition frameworks for connected health systems	Highlights importance of data quality, sensor selection, and interoperability in wearable systems	Limited discussion on cognitive/behavioral disorder-specific applications
Adeghe, E. P., Okolo, C. A., & Ojeyinka, O. T. (2024)	Survey of wearable healthcare technologies and monitoring systems	Demonstrates improved patient monitoring and healthcare efficiency using wearable devices	Lacks focus on advanced analytics and AI integration
Ates, H. C., Nguyen, P. Q., Gonzalez-Macia, L., Morales-Narváez, E., Güder, F., Collins, J. J., & Dincer, C. (2022)	End-to-end design framework for wearable sensors including materials, fabrication, and system integration	Emphasizes holistic design approach improving sensor accuracy and reliability	High complexity in implementation and scalability challenges
Yuan, H., Chan, S., Creagh, A. P., Tong, C., Acquah, A., Clifton, D. A., & Doherty, A. (2024)	Self-supervised learning for human activity recognition using large-scale wearable datasets	Achieves high accuracy using large-scale data and reduces dependency on labeled datasets	Requires extensive computational resources and large datasets

Table 1 provides an overview of the latest developments in the study of wearable technologies, with an emphasis on its approaches, applications, and important conclusions. All the studies underscore the increased significance of wearable devices in healthcare monitoring, especially in the fields of data collection, sensor architecture and smart analytics. Although review-based studies focus on system-level aspects, including interoperability and healthcare outcomes, recent studies combine more innovative machine learning applications, such as self-supervised learning to analyze behavior. But typical drawbacks are issue of scalability, insufficient domain specific attention to cognitive disorders and high computational needs. These loopholes reveal that the integrated AI-powered wearable system needs to be designed in a specific way to track cognitive and behavioural disorders in learners.

III. Smart Wearable Monitoring Framework

The suggested system architecture of smart wearable devices that will be used to track cognitive and behavioural disorders of students is a multi-layered, modular and scalable framework. It combines wearable sensors, smart data processing and cloud analytics to make it possible to monitor and detect cognitive and behavioral abnormalities in real time or early. The architecture is based on a structured pipeline, which has four significant layers: data acquisition layer, communication layer, data processing and analytics layer and application layer.

The base of the system is the data acquisition layer which comprises of a number of wearable sensors installed on wearable devices like smart watches, fitness bands, EEG headsets and smart garments. These sensors will take care of physiological and behavioral information of students in real-time. The main parameters are the heart rate variability (HRV), electrodermal activity (EDA), skin temperature,

motion (with accelerators and gyroscopes), and brain (EEG) activity. These are important indicators of cognitive and emotional conditions and therefore it allows detection of stress, anxiety, attention deficits along with other behavioural disorders. This layer is designed on the principle of non-intrusiveness, comfort and energy efficiency to allow continuous use in daily conditions like in classrooms and in homes. The raw data are sent using the communication layer that ensures that there is smooth integration between wearable and processing units. The protocols used in this layer are wireless communication protocols like Bluetooth Low Energy (BLE), Wi-Fi and IoT communication frameworks. The main purpose of this layer is to provide secure, reliable and low-latency data transmission. This stage can also adopt edge computing methods to perform pre-filtering and noise suppression to enable less computing by the centralized systems. It is especially relevant in the case of wearable devices where bandwidth and power consumption is a key limiting factor. The most important part of the system is the data processing and analytics layer, where the raw physiological and behavioral data is converted to significant insights. Several steps are involved in this layer and they include the preprocessing of data, feature extraction and classification. Noise filtering, signal normalization and artifact removal are some of the preprocessing techniques that are applied to guarantee the quality of the data. The extracted features are then inputted into feature extraction techniques which extract relevant indicators including statistical measures, frequency-domain features and time-series patterns of the signals obtained.

This layer uses advanced machine learning and deep learning models to consider the extracted features and categorise cognitive and behavioural states. Classification Baseline Classification Support vectors machines (SVM), decision trees, and random forests are the traditional machine learning algorithms that can be employed to work with simple and temporal data patterns. Deep learning Deep learning models, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), are capable of dealing with complex and temporal data patterns. The anomalies and events that may lead to certain disorders are detected and predicted with great accuracy with the help of these models. Also self-supervised and adaptive learning methods can be added to customize the system according to the behavior of individual students and hence enhance the model robustness and generalization. The analytics and processed data is stored and processed in the cloud-based platforms, which offers scaling, storage as well as computational capabilities. With the incorporation of cloud computing, data management can be centralized, which would be able to monitor long term and analyze trends. More so, cloud solutions enable real time synchronization and access, enabling healthcare professionals, teachers and caregivers to track the wellbeing of the students efficiently. The application layer is the interface and point of contact to a range of stakeholders such as the students, teachers, parents and healthcare professionals.

The system allows real-time data collection, smart analytics, and easy-to-use applications, which allow observing, detecting, and customizing intervention. Besides contributing to improving the efficiency of mental health monitoring, this architecture can be used to build smart learning spaces that can be oriented towards the well-being and academic performance of students.

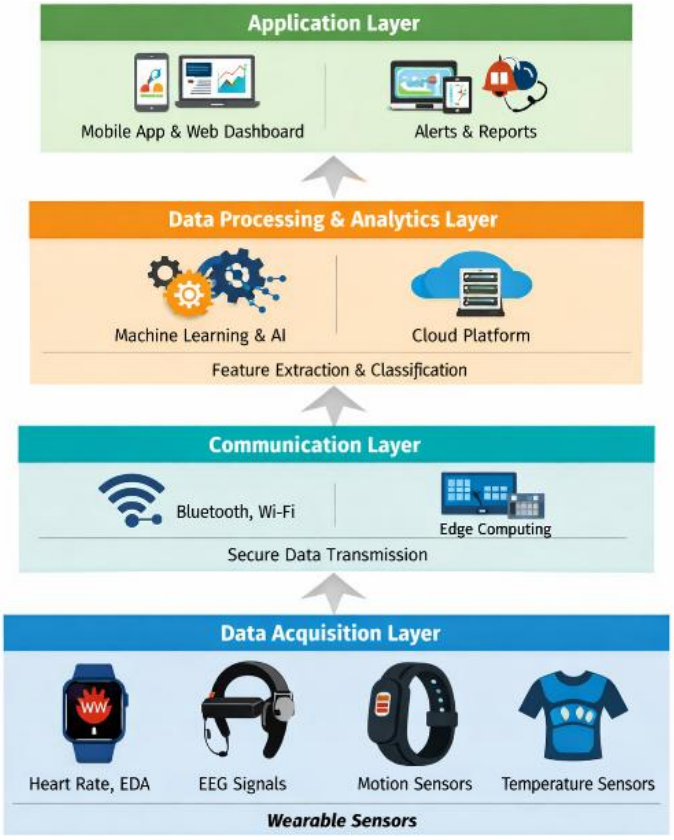

Figure 1. Framework for Smart Wearable Monitoring Devices

Figure 2 shows the data analytics pipeline of the system. Wearable sensor data are first cleaned and pre-processed, followed by the extraction and selection of features. The machine learning and deep learning models are used to analyze these features in order to classify cognitive states. Lastly, the system produces decision-making alerts, visualizations, and reports.

IV. Data Processing and Intelligent Analytics Model

The success of the suggested smart wearable monitoring system will greatly rely on how well it can process substantial amounts of physiological and behavioral data and transform them into valuable insights. The intelligent analytics model and data processing is important in detecting patterns, anomalies and predicting cognitive and behavioural disorders among students. The following section will provide a comprehensive description of the data processing pipeline, feature extraction methods, and machine learning models that will be used to perform intelligent analysis.

Data preprocessing is the initial phase in the analytics pipeline and guarantees the quality and reliability of the sensor data collected. Raw data collected by wearables devices are usually noisy, missing and motion artifacts by disturbances in the environment and the motions of the user. These issues are solved by preprocessing techniques such as filtering, normalization and signal smoothing. One such would be low-pass filters and high-pass filters to remove unwanted frequency content and normalization to put the data on a common scale. Moreover, it is also possible to divide the time-series data into smaller windows, which enables analyzing the patterns of time-related patterns of cognitive states effectively. The system then performs feature extraction after preprocessing which involves the extraction of useful features of raw sensor data. These properties can be defined in terms of time-domain and frequency-domain and statistical properties. Time-domain properties include mean, variance, standard deviation and peak values that tell about the behavior of the signal as a function of time. Periodicity and signal behavior are determined

by using frequency-domain features, which are calculated by such methods as Fast Fourier Transform (FFT).

Besides the conventional models, deep learning models have been of great concern in processing complex and high-dimensional data. Convolutional Neural Networks (CNNs) are most useful at extracting spatial features out of sensor data, whereas Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are most useful at analyzing sequential and time-series data. Temporal dependencies and patterns in physiological signals can be represented in these models and hence yield better prediction of behavioural anomalies. Moreover, hybrid architecture that involves CNN and LSTM can use both spatial and temporal features to achieve better performance. Self-supervised and adaptive learning is another developing method in wearable analytics that helps lessen the reliance on labeled data. Such methods enable the system to adapt to individual user behavior with time and learn on a large amount of unlabelled data. Monitoring students is particularly important as the reaction of physiological reactions can be quite variant in various students. Adaptive models can proceed to continually update themselves as new information is received and this improves the accuracy and robustness.

Health information in the system is sensitive and therefore, encryption algorithms and secure data storage options are embraced in order to protect user data. Machine learning techniques that are sensitive to privacy (such as federated learning) can be considered, too, to ensure that the data are decentralized yet can be used to train the models.

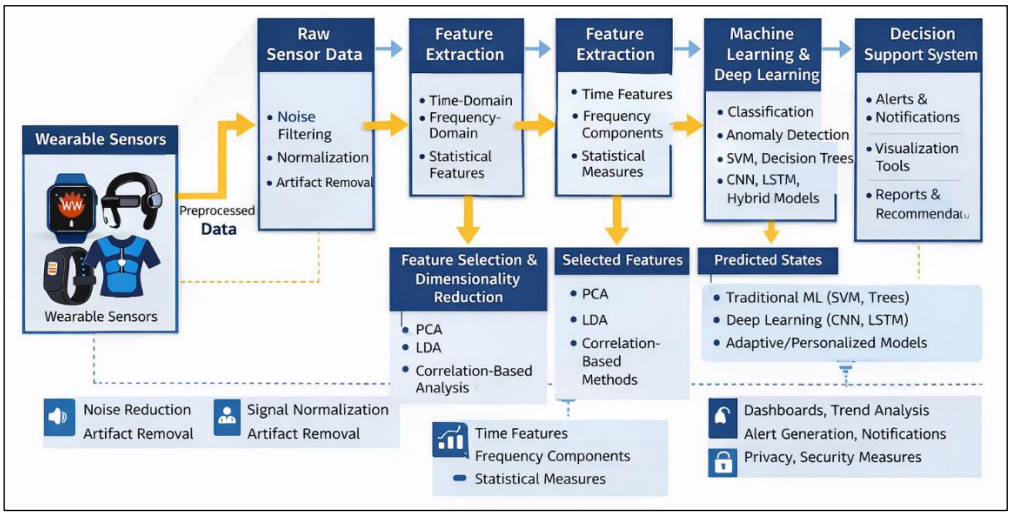

Figure 2. Data Processing and Intelligent Analytics Model

Figure 2 shows the data analytics pipeline of the system. Wearable sensor data is initially cleaned and preprocessed and subsequently features are extracted and selected. Machine learning and deep learning models are used to classify cognitive states with these features. Lastly, the system produces alerts, visualizations and reports to aid in decision-making.

V. Implementation and Experimental Setup

This part is the implementation details and experimental setup of proposed smart wearable monitoring system in order to detect cognitive and behavioural disorders among students. Its implementation consists of both hardware (wearable sensors), and software tools and machine learning frameworks in order to allow real-time acquisition of data, processing and analysis. The experimental set begins with the process of data collection during which wearable devices will be used to collect physiological and behavioral data. The devices that would be involved in the system would be heart rate sensors, electrodermal activity (EDA) sensors, accelerators and EEG headsets.

These sensors record important indications of stress, attention, emotional and exercise condition. In order to be reliable and consistent, data is gathered on controlled and semi realistic scenarios such as classrooms or lab on students. The rate of sampling of sensors is suitably set to trade off data and power conservation.

The preparation phase of the data consists of preparing data that is collected into structured forms that can be analyzed. The data comprises of multimodal time-series data that includes physiological and activity records. Each data point is classified according to a set of predetermined cognitive or behavioural states like stress, normal or relaxed. Labeling is done with the combination of self reports, observational measures and standardized psychological scales to make it accurate. The data is then separated into training, validation and testing to test the performance of the model. Different tools and frameworks are applied in the software implementation to process and analyze the data. Python is used as a programming environment with NumPy and Pandas to manipulate data, SciPy to process signals. The frameworks used to implement machine learning models are Scikit-learn with traditional algorithms and TensorFlow or PyTorch with deep learning models. Graphs and the trends of the data are generated and analyzed with the help of visualization tools like Matplotlib and Seaborn.

VI. Results and Comparative Analysis

This section will include the performance analysis of the proposed smart wearable monitoring system and will provide a comparative analysis on various machine learning and deep learning models which were applied in the detection of cognitive and behavioural disorders in students. The test is aimed at determining the accuracy, strength, and efficiency of the system to detect different cognitive states like stress, normal and abnormal behavioural patterns. The results of the experiment are obtained by means of the dataset that will be gathered with the help of wearable sensors and will consist of physiological data (heart rate variability, electrodermal activity, motion data, and EEG signals). Once the data has been preprocessed and features have been extracted, the data is then used to train and test various classification models. Standard measures, such as accuracy, precision, recall, F1-score, and area under the curve (AUC) are used to measure the performance of these models.

Based on the outcomes, deep learning models are better in terms of the classification accuracy and pattern recognition ability than traditional machine learning models. As an example, Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks are models that are more effective with time-series and multimodal data. CNN models are useful at defining the spatial pattern in physiological signals, whereas LSTM models are applicable in learning time-dependent patterns, which is why they are especially useful in behavioral analysis. The best performance is realised with hybrid models that use CNN and LSTM architectures since they use both spatial and temporal features.

Table 2. Comparative Analysis of Models

Method used	Accurateness	Exactness	Recollection	F1-Score
SVM	82	80	79	79
Decision Tree	78	76	75	75
Random Forest	85	83	82	82
CNN	91	90	89	89
LSTM	93	95.2	91	91
CNN-LSTM	96	95	95	95

As shown in Table 2, the classical machine learning algorithms such as Support Vector Machines (SVM), Decision Trees and Random Forests are good baseline algorithms but with less chance of modelling more nonlinear associations between high-dimensional data. Whereas SVM is appropriate in small data sets where there are clear lines, the Random Forest models may be more effective in generalization but computationally intensive when dealing with large data. Table VI summarises the results of each model and compares the performance of each model. The results have shown that the hybrid deep learning model suggested is the most precise followed by LSTM and CNN models. The traditional models have a relatively low accuracy but less computational power and hence fit well in resource-constrained settings.

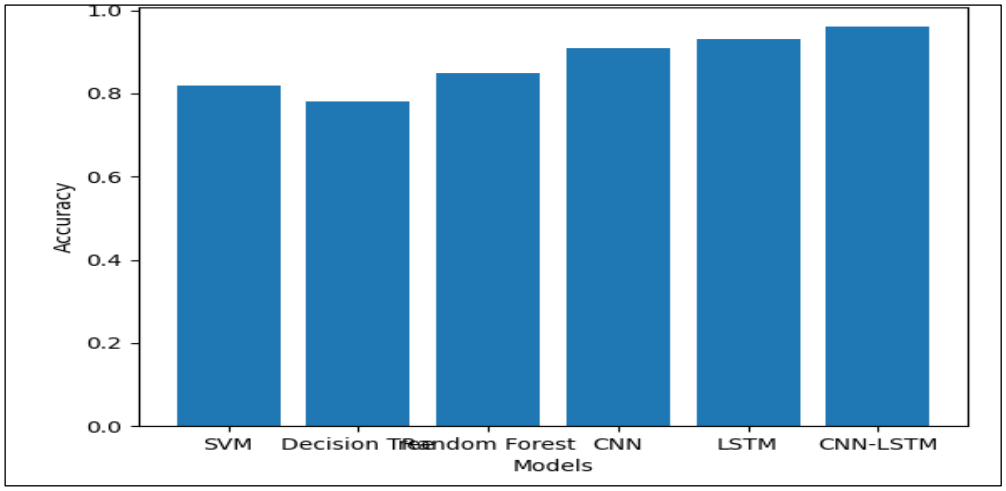

Figure 3. Model Accuracy Comparison

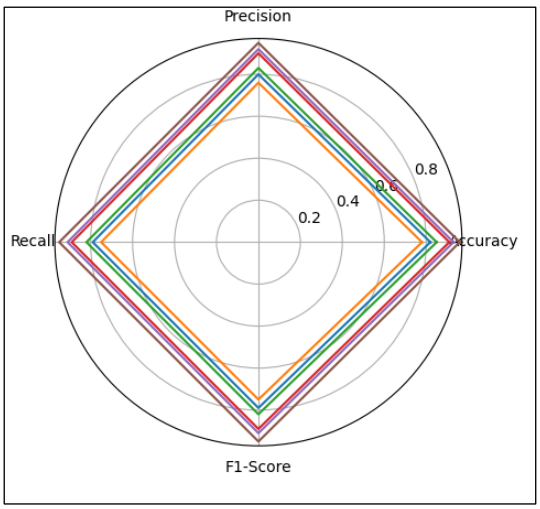

Figure 4. Model Performance

The graphical representations (Figures 3 and Figure 4) are used to see the model performance in various measures. These visualizations provide an easy comparison of the features of both strengths and weaknesses of models. One such example is the use of radar charts to illustrate that the deep learning models have equal performance on various metrics, and bar charts to illustrate the differences in accuracy and F1-scores of the various models. There is also a test of real-time detection of cognitive and behavioural anomalies in the system. The results indicate that the proposed system is applicable to identify abnormal patterns, such as elevated rates of stress and abnormal behavioral activity. Integration of real-time alerts will imply that these abnormalities are immediately reported to the involved parties and in this regard, appropriate measures are taken in time.

One of the fundamental aspects that will be examined is how the system will respond to the changing circumstances. The models are tested in different conditions which include the variation of sensor noise, extent of user activity and varying of the environment. The results indicate that deep learning models do not deteriorate in accuracy as the conditions get noisy as compared to the traditional models which slightly degrade. This demonstrates the importance of advanced learning processes in the control of variability of real world data. The computational efficiency of models also is analysed. More precise are deep learning models, which require additional computation and time to train. On the other hand, the classic models are easier to train and consume less resources, therefore, can be applied in edge computing. This is an accuracy-efficiency trade-off that is a vital factor in putting it into practice.

Further, the provided system is compared to the existing wearable-based monitoring technologies which are reported in the literature. The comparison shows that the proposed system, based on the integration of multimodal data and advanced analytics results in better detection accuracy and reliability. Individual differences in physiological responses are also a contribution to a better performance of the system since adaptive and personalized models take into account the individual differences.

VII. Applications and Case Studies

The cognitive and behavioural disorders monitored by using smart wearable devices have tremendous practical ramifications in schools. Uninterrupted monitoring of physiological and behavioral signals such as stress levels, attention levels, and moods can be monitored by wearable technology. Through intelligent algorithms, the system will be in a position to identify the early symptoms of disorders, such as anxiety, ADHD and depression. This early diagnosis can help teachers and medical personnel to intervene very early in life and prevent the emergence of such disorders and help students in a more constructive way. The other valuable application is at individualized learning and intervention process. The difference between the cognitive and behavioral patterns of each student is different and the difference can be recorded in real-time by wearable-based monitoring systems. With machine learning models, the system will be in a position to provide personalized data regarding learning habits, stressors and engagement of a student. This information can be used by the teachers to modify the teaching strategy depending on needs of each learner such as slowing down or picking up the teaching speed, providing more assistance or adding stress-reducing activities. Personalized interventions do not only have a beneficial influence on educational outcomes, but emotional stability and self-esteem of learners. The offered system can be easily incorporated into smart classrooms and e-learning as well. The internet of things (IoT) enabled systems, learning management systems and virtual learning tools can be implemented together with wearable device in the digital classroom of today. To illustrate this, wearable sensors have the potential to give real-time data to be used in monitoring student activity in online or hybrid classes. The system can trigger such adaptive measures as interactive content, breaks, or instructions to instructors in case a student displays fatigue and/or lack of focus. This integration enhances the degree of responsiveness, flexibility and student centrism of the entire learning process.

Several real life case studies and pilot projects have demonstrated the applicability of wearable technologies in behaviour and health monitoring. The devices have been successfully used in non-stop monitoring of the vital signs and rehabilitation processes in the health care facilities and this highlights their reliability and scalability. On the same note, mobile-based monitoring systems have been used to monitor mental illnesses and this has given useful feedback on the behavioral patterns with time. Such applications confirm the possibility of adapting such technologies to the educational environment to track the welfare of students. Pilot studies in schools have also presented encouraging findings, in which wearable devices could be utilized to monitor stress levels of students during tests and in the classroom. The results showed that real-time monitoring would be useful in detecting high-stress periods and therefore make it possible to intervene in time like counselling or relaxing methods. Also,

the systems have been applied to enhance engagement among students by detecting habits of distraction and inactivity.

VIII. Conclusion and Future Work

The rapid development of wearable technology, accompanied by smart data analytics, has revealed new opportunities in the area of cognitive and behavioural disorder monitoring in students. In this study, an all-inclusive model of the development and deployment of smart wearable devices that combine machine learning and cloud-based solutions to provide real-time and continuous monitoring of the physiological and behavioral states of the students was introduced. The proposed system will help overcome the main weaknesses of the conventional assessment systems as it offers objective and data-driven information that can be used to facilitate early diagnosis and intervention. The main contribution of this study includes the creation of a multi-layered architecture that incorporates the data acquisition, communication, intelligent analytics, and application layers into a single system. Multimodal data can be collected continuously with the use of wearable sensors like heart rate sensors, electro dermal activity sensors, motion sensors and EEG sensors. This information is analyzed with the help of advanced machine learning and deep learning algorithms, which allow recognising and predicting cognitive and behavioural disorders in the form of stress, anxiety, and attention-related disorders. The system also has increased capacity to accommodate individual differences among students because of the incorporation of adaptive and personalized learning models. Experimental results and statistical analysis indicated that deep learning algorithms, in particular, hybrid models with CNN and LSTM architecture are highly efficient to work with complex and time-series data in comparison with traditional machine learning algorithms. The models are more precise and generalize, hence can be applied to the real world. The paper, in addition, mentioned the trade-offs between the computational complexity and performance, which have to be optimized and efficient models to be implemented in practice.

In terms of application, the suggested system has vast implications on learning environments. The student tracking system will enable real-time monitoring of students and educators and healthcare professionals can provide timely guidance as the cognitive and behavioural issues are identified. E-learning systems, smart classrooms and a combination of wearable devices further enhances the learning process by providing a flexible and customized learning. It is not only a good method to improve academic results but also introduces emotional content and conscious of mental health to students. The proposed system has a potential that can be promising, but it has a number of challenges that need to be tackled in future studies. One of the most significant ones is the protection of the data privacy and security, particularly, sensitive health data of students. Strong encryption, data storage, and ethical principles should be used in order to protect the data of the users. In addition, issues of acceptance by the users, comfort of the devices, and usability in the long-term need to be tackled to ensure that wearable technologies are widely used in learning institutions. The next important limitation is the lack of consistency in the physiological cues in individuals that might affect the quality of forecasting models. Research work in the future must center on the creation of more powerful and individualized models that are able to adjust to individual variations. The federated learning and edge computing may also be taken into consideration to enhance data privacy but enable the training of the models successfully. Also, other sources of information such as behavioural logs, environmental context and academic performance indicators can be included to provide a more in-depth perspective of student wellbeing. Another option is to think of applying some new technology such as Internet of Things (IoT), digital twins, and explainable artificial intelligence (XAI) to work in the future to make the system more transparent and interpretable. The system will also be further realised by development of wearable devices that are energy efficient and have low powers. Moreover, large-scale applications of the proposed framework in real-life settings and longitudinal studies should

demonstrate its effectiveness and scalability in a range of educational settings.

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