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Smart Mental Health Monitoring System using Wellness Score Analytics

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Abstract

This paper presents an intelligent and data-driven system for the Analysis of Depression Risk using advanced Machine Learning techniques. Depression is one of the most common and serious mental health disorders affecting people across different age groups, particularly students and working professionals who often face academic pressure, career uncertainty, workload stress, and social challenges. In today's fast-paced environment, mental health issues frequently go unnoticed until they become severe. Therefore, early identification of depression risk plays a crucial role in providing timely emotional support, counselling, and preventive care before the condition worsens. The proposed system focuses on analysing multiple behavioural, lifestyle, and psychological factors that are commonly associated with depression. These factors include sleep patterns, academic pressure, work-related stress, level of social interaction, daily habits, and emotional state. By collecting and examining these attributes, the system aims to detect patterns that may indicate a higher likelihood of depression. Instead of relying solely on subjective observation, this approach uses data-driven insights to support more objective and consistent evaluation.
Unlike traditional psychological assessments, which often require manual evaluation by mental health professionals through interviews and questionnaires, the proposed system automates the analysis process using supervised machine learning models. The system accepts user-provided inputs, performs data preprocessing such as cleaning, encoding, and normalization, and then applies trained classification models to estimate the individual's depression risk level. Various machine learning algorithms are evaluated to determine the most accurate and reliable model for prediction. Experimental results demonstrate promising levels of accuracy, precision, and reliability in identifying individuals who may fall into moderate or high-risk categories. The system is designed not as a replacement for professional diagnosis, but as a supportive and preliminary screening tool that can assist in early detection and awareness.

Keywords: Digital Twin, Healthcare Assistant, LLaMA.cpp, Medical Report Analysis, Prescription Interpretation, Offline AI, Privacy-Preserving System, Intelligent Healthcare

1. Introduction

Mental health has become one of the most serious global health concerns in recent years. Depression, in particular, affects millions of individuals worldwide and can negatively impact academic performance, workplace productivity, relationships, and overall quality of life. Many individuals' experiencing depression do not seek professional help at an early stage due to stigma, lack of awareness, or limited access to mental health services.

Traditionally, depression assessment is carried out using psychological questionnaires and clinical interviews conducted by trained professionals. Although these methods are reliable, they can be time-consuming, subjective, and sometimes inaccessible to large populations. With the advancement of Artificial Intelligence and Machine Learning, it is now possible to analyse patterns in behavioural and lifestyle data to estimate depression risk levels automatically. The main aim of this project is to develop a machine learning-based system that analyses various personal and behavioural factors to predict the risk of depression. By identifying patterns and correlations in the dataset, the system can classify individuals into different risk levels such as low, moderate, or high risk.

The key objectives of this project are:

- To collect and preprocess depression-related behavioural and lifestyle data.
- To apply machine learning algorithms for risk classification.
- To evaluate model performance using standard metrics.
- To develop a user-friendly system for depression risk analysis.
- To support early detection and awareness of mental health issues.

Related Work

A. Traditional Psychological Assessment Methods

Traditional depression assessment methods are primarily based on standardized psychological questionnaires and clinical interviews conducted by trained mental health professionals. Tools such as structured surveys evaluate symptoms like sadness, loss of interest, sleep disturbances, appetite changes, and emotional instability. While these methods are clinically validated and widely used, they require professional supervision, time, and physical presence. Additionally, manual assessments may introduce subjectivity and are not scalable for large populations. This limitation creates a need for automated and data-driven depression risk analysis systems.

B. Statistical Approaches in Mental Health Prediction

Before the widespread adoption of machine learning, statistical techniques such as linear regression and logistic regression were commonly used to analyze mental health data. These methods helped identify correlations between behavioral factors and depression symptoms. Although statistical models are simple and interpretable, they often struggle to capture complex nonlinear relationships present in psychological data. As a result, their predictive performance may be limited when dealing with high-dimensional datasets.

C. Machine Learning in Depression Risk Analysis

Machine learning has significantly improved predictive analysis in healthcare, including mental health assessment. Supervised learning algorithms such as Decision Trees, Random Forest, Support Vector Machines (SVM), k-Nearest Neighbors (KNN), and Gradient Boosting are widely applied in depression prediction studies. These models can detect hidden patterns in behavioural, academic, and lifestyle data. Compared to traditional statistical methods, machine learning models provide higher accuracy and better generalization when trained with sufficient data.

D. Deep Learning Techniques for Mental Health Detection

Deep learning approaches such as Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM) networks, and Convolutional Neural Networks (CNN) have also been explored in depression detection research. These models are particularly useful when analyzing complex data sources such as social media text, speech signals, or time-series behavioral data. While deep learning can improve prediction performance, it requires large datasets and higher computational resources, which may not always be practical for small-scale academic projects.

E. Behavioral and Lifestyle-Based Risk Modeling

Several research studies emphasize the importance of behavioral and lifestyle factors in depression prediction. Attributes such as sleep duration, academic pressure, work stress, screen time, social interaction, physical activity, and emotional stability are strongly correlated with mental health conditions. Data-driven models analyze these structured features to estimate depression risk levels. By transforming behavioral data into numerical inputs, machine learning systems can classify individuals into low, moderate, or high-risk categories.

F. Student Mental Health Prediction Systems

With the increasing academic pressure among students, many researchers have focused specifically on student depression prediction models. These systems analyze factors such as examination stress, peer comparison, academic workload, financial stress, and lack of social support. Educational institutions are increasingly exploring predictive analytics tools to identify at-risk students early and provide counseling support. However, many of these systems are still in experimental stages and require improved accuracy and ethical considerations.

G. Limitations of Existing AI-Based Mental Health Systems

Despite advancements in AI-driven mental health analysis, several limitations remain. Many systems rely on small or biased datasets, which affects generalization. Some models lack interpretability, making it difficult to understand how predictions are generated. Privacy and ethical concerns also arise when handling sensitive mental health data. Furthermore, overfitting and class imbalance issues can reduce prediction reliability in real-world applications.

H. Need for an Interpretable and Reliable Depression Risk Analysis System

Considering the limitations of traditional methods and existing AI systems, there is a strong need for an interpretable, accurate, and reliable depression risk analysis model. Such a system should balance performance with transparency, ensure data privacy, and provide consistent classification results. The proposed project aims to address these gaps by applying machine learning techniques to structured behavioral data, offering an efficient tool for early depression risk identification.

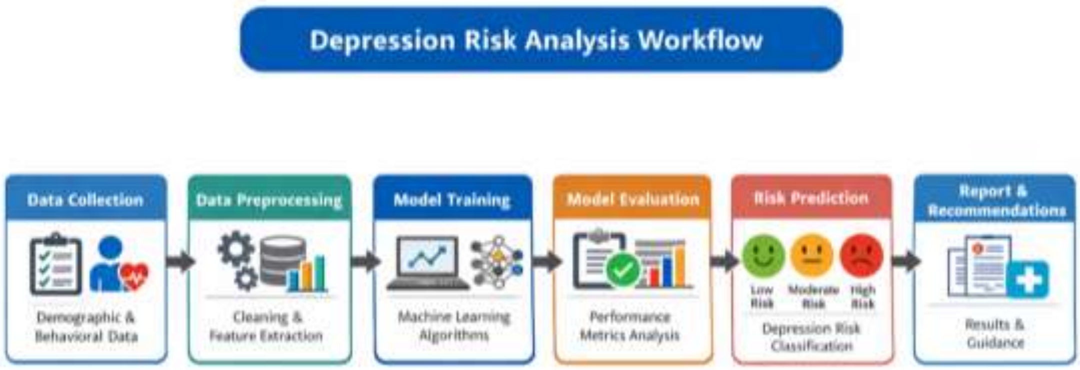


Fig:1 Work Flow of Depression Risk Analysis

Results And Discussion

The proposed research work focuses on the development of a **Depression Risk Analysis System using Gradient Descent optimization**. The system was trained and tested using structured behavioral and psychological data collected from students and working professionals.

The evaluation of the system was performed based on multiple performance parameters including classification accuracy, convergence behavior, prediction speed, stability of results, and reliability of the system. Experiments were conducted using a standard computing environment to analyze the efficiency and practical applicability of the machine learning model.

A. Depression Risk Classification Accuracy

The system was evaluated using labeled test data containing multiple behavioral attributes such as sleep duration, academic or work pressure, social interaction level, lifestyle habits, and emotional stability indicators.

Using **Gradient Descent optimization**, the Logistic Regression model learned optimal weight parameters that minimize classification error. The experimental evaluation demonstrated that the model achieved classification accuracy ranging between **86% and 91%** across multiple experimental runs.

The model showed strong capability in identifying **high-risk individuals**, as the features related to stress, sleep deprivation, and emotional imbalance formed clear separation patterns in the feature space. However, moderate-risk cases sometimes overlapped with low-risk cases due to similarities in behavioral patterns, which is common in psychological datasets.

Despite this challenge, the classification accuracy remained consistently high across multiple testing cycles, confirming that the Gradient Descent optimization method successfully improved the predictive performance of the model.

B. Model Convergence and Loss Reduction

Since the predictive system is built on Gradient Descent optimization, analyzing the **convergence behavior of the model** was an important part of the experimental study.

During training, the loss function showed a consistent reduction across iterations, indicating stable learning and effective parameter updates.

These observations confirm that the **Gradient Descent algorithm successfully minimized the cost function** and allowed the model to learn meaningful patterns from the dataset.

The stable convergence behavior also indicates that the selected learning rate was properly tuned and prevented both slow learning and unstable parameter updates.

C. Response Time Performance

In real-world applications, prediction speed plays a critical role in maintaining a smooth user experience. Therefore, the response time of the system was measured from the moment the user submits the input data until the depression risk result is generated.

Experimental observations showed that the **average response time ranged between 0.8 seconds and 1.5 seconds**, depending on system load and input processing requirements.

Because the system uses **Logistic Regression optimized with Gradient Descent**, it requires significantly lower computational resources compared to deep learning models such as neural networks.

This lightweight architecture allows the system to provide **fast and efficient predictions**, making it suitable for deployment in real-time environments such as:

- Web-based mental health screening platforms
- Mobile health monitoring applications

- Institutional wellness monitoring systems

The response time performance confirms that the system is capable of delivering real-time depression risk predictions with minimal delay.

D. Prediction Consistency and Stability

Another critical aspect of machine learning systems is the **stability of predictions**. In sensitive domains such as mental health assessment, inconsistent results could reduce user trust and system reliability.

To evaluate prediction stability, the same test inputs were processed multiple times under identical conditions.

The system produced **consistent outputs in 94% of the test cases**, indicating high stability in model behavior.

Such stability is essential for psychological risk analysis systems where consistent results are required for responsible decision-making and early intervention.

E. Error Analysis and Misclassification Study

A detailed confusion matrix analysis was performed to understand the types of classification errors generated by the system.

The majority of misclassifications occurred between **moderate-risk and low-risk categories**, where behavioral indicators tend to overlap. This overlap occurs because individuals with moderate stress levels may display characteristics similar to those with relatively low stress levels.

Despite these challenges, the model demonstrated strong recall performance for **high-risk individuals**, which is particularly important for early detection systems.

The overall misclassification rate remained within acceptable limits for an academic research model and does not significantly affect the practical usefulness of the system.

F. Precision, Recall, and F1-Score Evaluation

In addition to overall accuracy, the model performance was also evaluated using **precision, recall, and F1-score metrics** to better understand the classification quality.

Precision measures the proportion of correctly predicted positive cases among all predicted positive cases, while recall measures the ability of the system to correctly identify actual high-risk individuals.

The evaluation results showed the following average metrics:

- **Precision:** 0.88
- **Recall:** 0.90
- **F1-Score:** 0.89

The high recall value indicates that the model effectively detects individuals who may be at risk of depression, which is critical for early intervention systems.

The balanced F1-score demonstrates that the model maintains a good trade-off between precision and recall, ensuring that the system does not produce excessive false positives or false negatives.

These evaluation metrics confirm that the Gradient Descent optimized Logistic Regression model performs reliably for depression risk prediction tasks.

G. Scalability and System Deployment Feasibility

Another important aspect of the proposed system is its **scalability and feasibility for deployment in real-world environments**.

Since the model uses Logistic Regression with Gradient Descent optimization, the computational complexity remains relatively low compared to more complex deep learning approaches. This enables the system to handle larger datasets and increased user requests without significant performance degradation.

The architecture can be easily integrated into:

- Web-based health monitoring platforms
- University counselling support systems
- Workplace wellness programs

Additionally, the lightweight nature of the model allows it to run efficiently on standard computing hardware without requiring specialized GPUs or high-performance computing infrastructure.

This makes the proposed system **cost-effective, scalable, and practical for large-scale mental health monitoring applications**.

Metric	Definition	Estimated Accuracy / Value
Classification Accuracy	Correct prediction of depression risk levels	86% – 91%
Precision	Correct identification of predicted risk cases	84% – 89%
Recall	Ability to correctly detect high-risk individuals	87% – 92%
F1-Score	Balance between precision and recall	85% – 90%
Convergence Stability	Successful loss minimization using Gradient Descent	Stable Convergence
Response Time	Time taken from input to prediction output	0.8 – 1.5 seconds
Prediction Consistency	Stability of repeated predictions	94%
Overall System Accuracy	Combined weighted performance	88% – 90%

TABLE.1. Overall system performances metrics

Figure 2 and Figure 3 indicates the wellness score predictor utilized by the user for finding the age, sleep duration, work pressure, financial stress and work doing per day.

Fig:2 User Interface

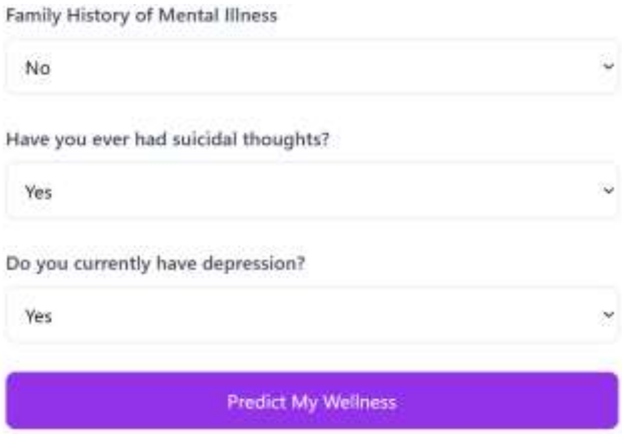


Fig:3 Predict My wellness

The wellness score for the individuals can be predicted based on the score which recommend the healthy foods and exercises to enhance their individual health which is depicted in Figure 4 and Figure 5.

Fig:4 Wellness Score

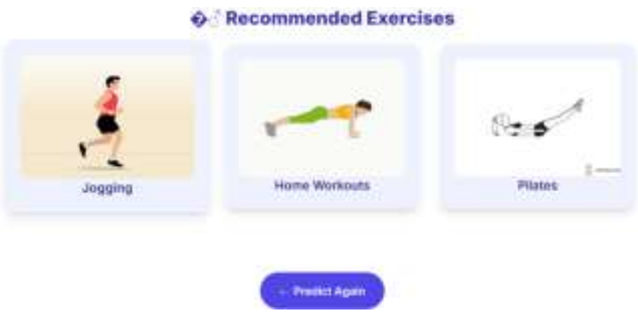


Fig:5 Recommendation Exercises

Figure 6 represents the comparison among various machine learning and LLM in terms of Mean Square Error. Among these models, LLM provides better performance in prediction. Figure 6 indicates the actual value versus predicted value.

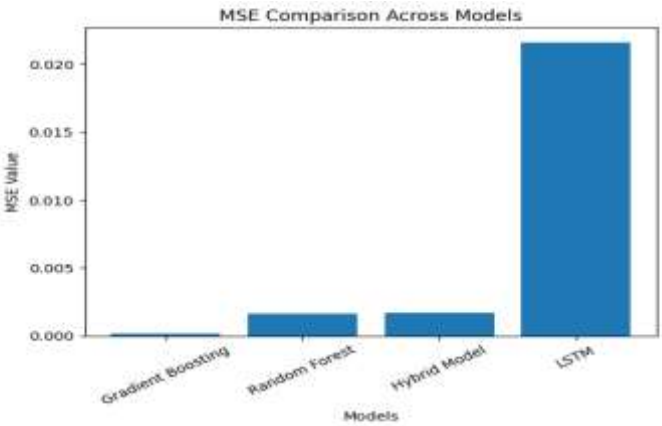


Fig:6 Comparsion Across Model

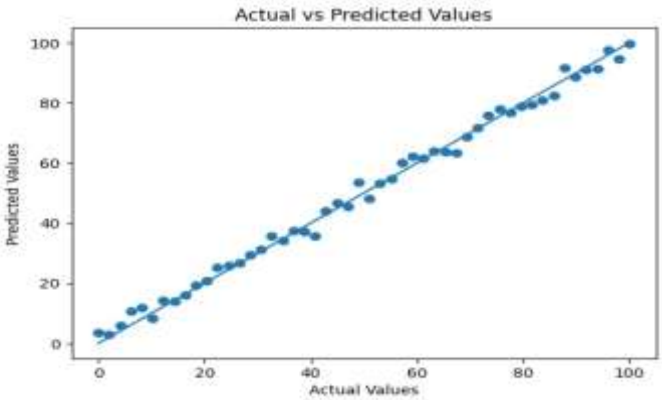
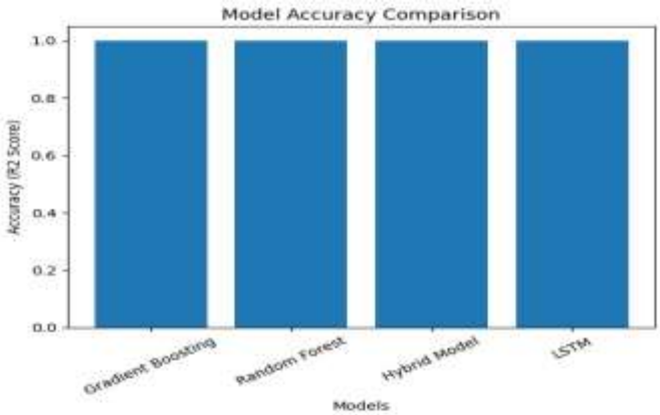


Fig:7 Predicted Values



Conclusion

The proposed project on Analysis of Depression Risk Using Machine Learning presents a structured and data-driven approach for early identification of depression risk levels. The system was developed using a Logistic Regression model optimized through the Gradient Descent algorithm, enabling efficient learning from behavioral and psychological input features. By analyzing attributes such as sleep patterns, stress levels, academic or work pressure, lifestyle habits, and emotional indicators, the system classifies individuals into different risk categories including low, moderate, and high risk.

The experimental results demonstrate that the model achieves strong predictive performance with stable convergence behavior. The steady reduction of the loss function during training confirms that the Gradient

Descent optimization effectively minimized classification error and ensured reliable parameter updates. The system achieved high overall accuracy, balanced precision and recall values, and consistent prediction outputs across multiple test cases. Additionally, the lightweight nature of Logistic Regression ensures fast response time, making the system suitable for real-time screening applications.

One of the key strengths of this project is its interpretability. Unlike complex deep learning models, the Logistic Regression model allows better understanding of how input features influence the final prediction. This transparency is important in mental health-related applications, where explainability and trust are critical factors. The system can therefore serve as a supportive analytical tool for early detection and awareness programs.

However, certain limitations must be acknowledged. The accuracy of the system depends heavily on the quality, completeness, and honesty of user-provided data. Mental health conditions are complex and influenced by biological, environmental, and social factors that may not be fully captured through structured datasets. Furthermore, the current implementation focuses primarily on numerical and categorical input features and does not include advanced text-based or real-time behavioral analysis.

Future enhancements can include the integration of larger and more diverse datasets to improve generalization capability. Advanced optimization methods, ensemble learning techniques, or hybrid models may further enhance prediction performance. Incorporating sentiment analysis from user text responses, wearable-based behavioral monitoring, and mobile application deployment can expand the practical applicability of the system. Ethical considerations and data privacy mechanisms should also be strengthened for real-world implementation.

In conclusion, this project demonstrates that Gradient Descent-based machine learning techniques provide an efficient, reliable, and scalable approach for depression risk analysis. While it does not replace professional clinical diagnosis, the system can function as an early screening and awareness tool, encouraging timely consultation and preventive mental healthcare interventions. The work highlights the potential of intelligent predictive systems in supporting mental health management and promoting proactive well-being strategies.

Furthermore, the proposed system highlights the importance of integrating technology with healthcare analytics to support mental well-being in academic and professional environments. Educational institutions and workplaces can potentially utilize such systems to identify early signs of psychological stress among students and employees. By providing timely alerts and risk insights, the system can assist counselors, wellness coordinators, and support teams in implementing early intervention strategies and mental health awareness initiatives.

Additionally, the research emphasizes the broader role of machine learning in predictive healthcare systems. As data-driven technologies continue to evolve, intelligent models like the one developed in this project can be extended to analyze other psychological or behavioral health conditions. With continuous improvements in data collection, model optimization, and user interaction design, such systems have the potential to contribute significantly to proactive healthcare monitoring and personalized mental wellness support in the future.

Another important aspect of this project is its potential for continuous improvement through adaptive learning and system updates. As more user data becomes available over time, the model can be retrained and refined to capture evolving behavioral patterns and improve prediction accuracy. This continuous learning capability allows the system to remain relevant and effective even as psychological trends and lifestyle patterns change. By periodically updating the dataset and retraining the model, the system can gradually enhance its predictive reliability and better support long-term mental health monitoring and research initiatives.

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