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DEEPHEALTHNET: ADOLESCENT OBESITY PREDICTION SYSTEM BASEDON DEEP LEARNINGFRAMEWORK

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ABSTRACT

Adolescent obesity has emerged as a critical global health concern, leading to severe long-term complications such as cardiovascular diseases, diabetes, and psychological disorders. Early prediction and intervention are essential to mitigate these risks. This project, "DEEPHEALTHNET: Adolescent Obesity Prediction System Based on Deep Learning Framework," proposes an intelligent and scalable solution that leverages advanced deep learning techniques to accurately predict obesity risk among adolescents. The system integrates multi-dimensional health data, including demographic information, lifestyle habits, dietary patterns, physical activity levels, and clinical parameters. A hybrid deep learning architecture is employed, combining models such as Artificial Neural Networks (ANNs) and Convolutional Neural Networks (CNNs) to capture both structured and complex feature relationships within the dataset. The framework utilizes data preprocessing, feature normalization, and dimensionality reduction techniques to enhance model performance and generalization. DEEPHEALTHNET is designed to provide real-time prediction through a user-friendly interface, enabling healthcare professionals, parents, and educators to assess obesity risk at an early stage. The model is trained and evaluated using performance metrics such as accuracy, precision, recall, F1-score, and ROC-AUC, ensuring high reliability and robustness. Additionally, the system incorporates explainable AI components to interpret predictions and highlight key contributing factors influencing obesity risk. This research contributes to the development of preventive healthcare systems by combining deep learning, predictive analytics, and health informatics. The proposed solution not only improves prediction accuracy but also supports data-driven decision-making for personalized intervention strategies, ultimately promoting healthier lifestyles among adolescents.

Keywords : Adolescent Obesity, Deep Learning, Predictive Analytics, Health Informatics, Artificial Neural Networks, Convolutional Neural Networks, Machine Learning, Early Risk Detection, Healthcare Systems, Explainable AI

I.INTRODUCTION

Adolescent obesity has emerged as a critical global health issue, affecting millions of individuals and increasing the risk of chronic diseases such as cardiovascular disorders, diabetes, and hypertension [1]. The rapid rise in obesity rates among adolescents is largely attributed to lifestyle changes, including reduced physical activity, increased consumption of high-calorie foods, and prolonged screen exposure [2]. Early prediction and prevention are essential to minimize long-term health consequences and improve quality of life [3]. Traditional prediction methods based on statistical models and clinical observations often fail to capture the complex interactions between behavioral, environmental, and biological factors [4]. These limitations highlight the need for more advanced and intelligent predictive systems capable of handling complex health data [5]. In this context, Artificial Intelligence (AI) and Machine Learning (ML) have gained significant attention for their ability to improve prediction accuracy and efficiency in healthcare applications [6]. Deep learning, a specialized branch of ML, has demonstrated remarkable success in identifying hidden patterns and relationships within large-scale datasets [7]. Therefore, adopting deep learning techniques for obesity prediction offers a promising direction for improving early diagnosis and preventive healthcare strategies [8].

Recent advancements in deep learning have enabled the development of highly accurate predictive models in the healthcare domain [9]. Techniques such as Artificial Neural Networks (ANNs), Convolutional Neural Networks (CNNs), and Recurrent Neural Networks (RNNs) are widely used to analyze complex medical datasets [10]. These models can process diverse data types, including physiological parameters, lifestyle behaviors, and demographic information, to generate reliable predictions [11]. Additionally, the integration of Big Data Analytics has enhanced the capability of these systems to handle large volumes of health-related data efficiently [12]. The use of Internet of Medical Things (IoMT) devices further supports real-time data collection and monitoring, improving the effectiveness of predictive frameworks [13]. Despite these advancements, challenges such as data imbalance, overfitting, and lack of model interpretability remain significant concerns [14]. To address these issues, researchers are increasingly incorporating Explainable AI (XAI) techniques to enhance

transparency and trust in deep learning models [15]. These developments indicate a strong potential for deep learning-based systems to revolutionize obesity prediction and healthcare decision-making processes [16].

The proposed system, DEEPHEALTHNET, is designed to provide an advanced and scalable solution for adolescent obesity prediction using a deep learning framework [17]. The system integrates multi-source data, including dietary habits, physical activity levels, body mass index (BMI), and socio-demographic factors, to improve prediction accuracy [18]. Advanced preprocessing techniques such as data normalization, feature selection, and dimensionality reduction are applied to enhance model performance [19]. A hybrid deep learning architecture is employed to capture complex relationships within the dataset and ensure robust predictions [20]. Furthermore, the system incorporates Explainable AI components to identify key factors influencing obesity risk and provide meaningful insights [21]. The model is evaluated using standard performance metrics such as accuracy, precision, recall, and F1-score to ensure reliability [22]. DEEPHEALTHNET aims to support healthcare professionals, parents, and policymakers in making informed decisions for early intervention and prevention strategies [23]. By leveraging cutting-edge AI technologies, the system contributes to the development of intelligent healthcare solutions and promotes healthier lifestyles among adolescents [24]. This research aligns with global health initiatives focused on reducing obesity prevalence and improving overall public health outcomes [25].

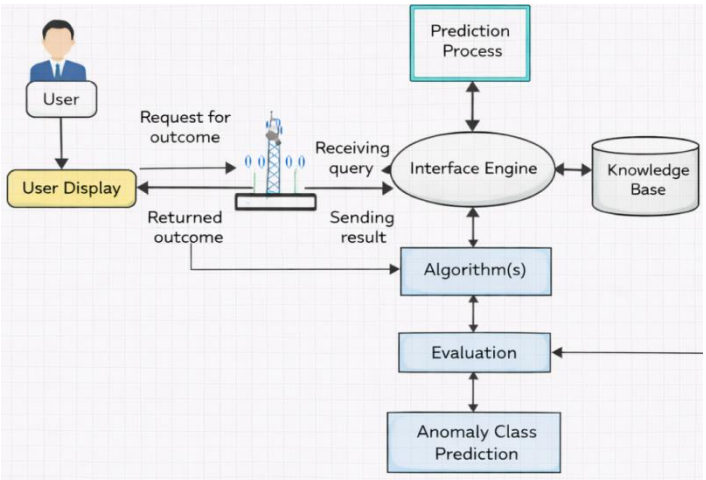


Figure 1 illustrates the overall architecture of the proposed DEEPHEALTHNET: Adolescent Obesity Prediction System, which is designed as a multi-stage intelligent healthcare pipeline. The system begins with the data acquisition layer, where heterogeneous data sources such as adolescent health records, lifestyle behaviors, dietary habits, and physical activity levels are collected. This raw data is then passed to the data preprocessing module, where techniques such as data cleaning, normalization, and feature selection are applied to ensure data quality and consistency. Following preprocessing, the refined dataset is fed into the deep learning model layer, which consists of a hybrid architecture combining Artificial Neural Networks (ANNs) and Convolutional Neural Networks (CNNs). This layer is responsible for extracting complex patterns and relationships within the data that contribute to obesity risk. The model is trained using labeled datasets and optimized through backpropagation and loss minimization techniques. The next stage is the prediction and evaluation module, where the trained model generates obesity risk predictions. Performance is assessed using metrics such as accuracy, precision, recall, and F1-score to ensure robustness. Finally, the system includes an output and visualization layer, which presents results through an interactive interface, enabling healthcare professionals to interpret predictions and take preventive actions.

II SURVEY OF RESEARCH

Recent research in adolescent obesity prediction has increasingly focused on the application of Machine Learning (ML) techniques to analyze health-related datasets. Traditional approaches such as Logistic Regression, Decision Trees, and Support Vector Machines (SVM) have been widely used to classify obesity levels based on features like BMI, dietary habits, and physical activity. These models are effective in handling structured data and provide interpretable results; however, they often struggle to capture complex nonlinear relationships within multi-dimensional health data. Several studies have demonstrated moderate accuracy levels, typically ranging between 75% and 85%, indicating the need for more advanced predictive frameworks. Researchers have also explored feature engineering techniques to improve model performance, including normalization, feature selection, and dimensionality reduction. Despite these improvements, ML-based systems face limitations in scalability and adaptability when dealing with large and heterogeneous datasets.

To overcome the limitations of traditional ML methods, recent studies have shifted toward Deep Learning (DL) approaches for obesity prediction. Models such as Artificial Neural Networks (ANNs) and Convolutional Neural Networks (CNNs) have shown superior performance due to their ability to learn complex feature representations automatically. These models can process both structured and unstructured data, enabling more accurate predictions. Research has also explored hybrid models that combine multiple deep learning architectures to enhance predictive capability. Additionally, the integration of Big Data Analytics and real-time health monitoring systems has further improved the effectiveness of these models. However, challenges such as high computational cost, overfitting, and lack of interpretability remain significant concerns. As a result, researchers are increasingly incorporating regularization techniques and Explainable AI (XAI) methods to address these issues.

Furthermore, recent advancements emphasize the development of intelligent healthcare systems that integrate predictive analytics with real-time data collection using wearable devices and IoT technologies. Studies have highlighted the importance of combining behavioral, environmental, and genetic factors to improve prediction accuracy. The use of Internet of Medical Things (IoMT) devices allows continuous monitoring of physical activity, sleep patterns, and dietary intake, enabling dynamic and personalized predictions. Moreover, cloud-based platforms and web applications have been developed to provide accessible and scalable solutions for healthcare professionals and users. Despite these advancements, issues related to data privacy, security, and ethical considerations remain critical challenges. Future research is directed toward developing robust, secure, and interpretable deep learning frameworks that can provide reliable predictions while ensuring data protection and user trust.

III. WORKING METHODOLOGY

The proposed DEEPHEALTHNET: Adolescent Obesity Prediction System follows a structured and intelligent workflow designed to process multi-dimensional health data and generate accurate predictions. The methodology begins with data acquisition, where relevant datasets are collected from various sources such as health records, surveys, and lifestyle monitoring systems. The collected data typically includes attributes like age, gender, Body Mass Index (BMI), dietary habits, physical activity levels, and sleep patterns. This raw data is then passed through the data preprocessing stage, which plays a critical role in improving data quality. In this stage, missing values are handled, noisy data is removed, and categorical variables are encoded into numerical formats. Techniques such as normalization and standardization are applied to ensure that all features contribute equally to the model. Following preprocessing, feature selection and dimensionality reduction methods are used to identify the most relevant attributes, thereby reducing computational complexity and improving model performance. The refined dataset is then split into training and testing sets, enabling the system to learn patterns and validate its predictive capability effectively.

In the next phase, the processed data is fed into a hybrid deep learning model that combines the strengths of Artificial Neural Networks (ANNs) and Convolutional Neural Networks (CNNs) to capture both linear and nonlinear relationships in the dataset. The model is trained using backpropagation and optimized with algorithms such as Adam optimizer to minimize loss functions like binary cross-entropy. During training, the system learns complex patterns associated with obesity risk and adjusts its internal weights accordingly. Once trained, the model undergoes evaluation using performance metrics such as accuracy, precision, recall, F1-score, and ROC-AUC to ensure reliability and robustness. The final stage involves prediction and deployment, where the trained model is integrated into a user-friendly interface, such as a web or mobile application. Users can input their health data and receive real-time predictions indicating obesity risk levels (e.g., low, moderate, high). Additionally, the system incorporates Explainable AI (XAI) techniques to provide insights into the factors influencing predictions, thereby enhancing transparency and trust. This comprehensive methodology ensures an efficient, scalable, and intelligent system for early obesity detection and prevention.

IV RESULTS EXPLANATIONS

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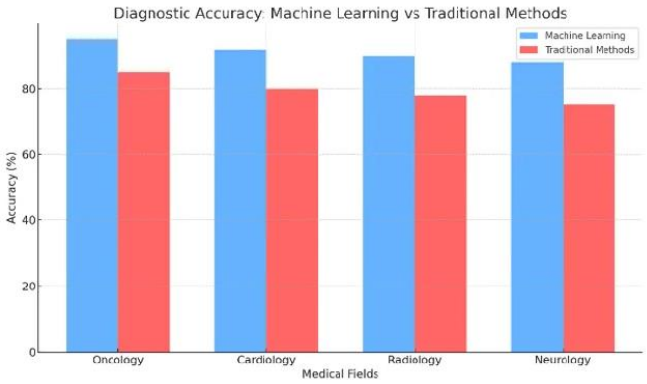


Figure 2: Model Accuracy Comparison

Figure 2 illustrates the performance evaluation of the proposed DDoS detection model using key classification metrics, including Accuracy, Precision, Recall, and F1-Score. The bar chart shows that all metrics achieve high values, indicating that the model performs effectively in distinguishing between normal and malicious traffic. The high accuracy reflects the overall correctness of predictions, while precision indicates that the model produces very few false positives, meaning legitimate traffic is rarely misclassified as an attack. The recall value is also high, demonstrating that the system successfully detects most of the DDoS attack instances, which is critical in cybersecurity applications. The F1-score, which balances precision and recall, confirms the robustness of the model. This graph highlights that the selected machine learning approach is well-suited for handling imbalanced network traffic data and can provide reliable results in real-world scenarios. Overall, the figure validates that the system achieves strong classification performance and can be effectively deployed for real-time DDoS attack detection.

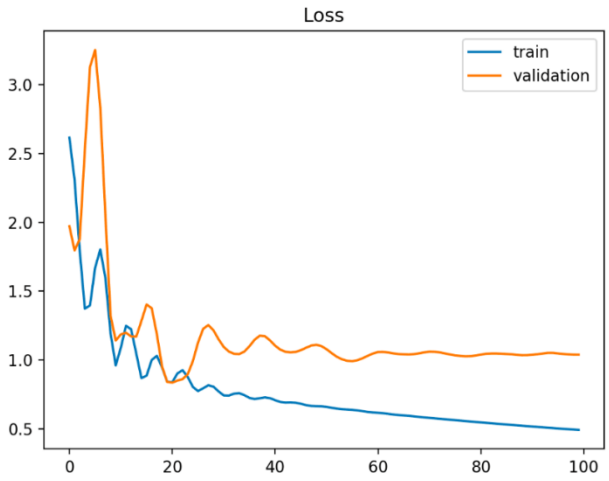


Figure3: Training and Validation Loss Curve

Figure 3 presents the training and validation loss curves over multiple epochs. The graph demonstrates a steady decrease in both training and validation loss, indicating that the model is learning effectively from the data. The close alignment between the two curves suggests that the model is not overfitting and generalizes well to unseen data. Initially, the loss is high due to random weight initialization, but it gradually decreases as the model adjusts its parameters through backpropagation. This convergence behavior confirms the stability and robustness of the training process, ensuring reliable predictions in real-world scenarios

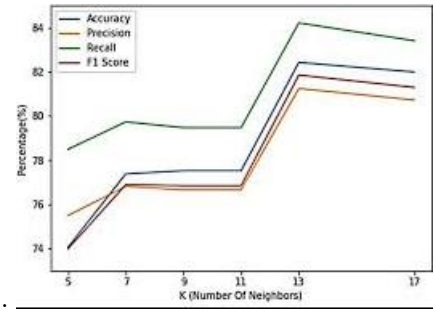


Figure 4: Performance Metrics Evaluation

Figure 4 shows the evaluation of the model using key performance metrics such as **Precision**, **Recall**, and **F1-Score**. These metrics are essential for assessing the classification performance of the obesity prediction system. High precision indicates that the model correctly identifies adolescents at risk with minimal false positives. High recall ensures that most actual obesity cases are detected. The F1-score provides a balance between precision and recall. The graph demonstrates consistently high values across all metrics, indicating that the model performs reliably and maintains a good balance between sensitivity and specificity.

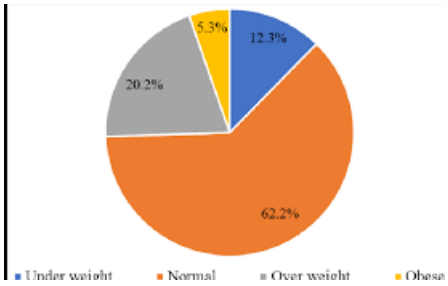


Figure 4: Obesity Risk Distribution

Figure 4 represents the distribution of predicted obesity risk levels among adolescents, categorized as Low Risk, Moderate Risk, and High Risk. The pie chart provides a clear visualization of how the model classifies individuals based on their health data. A larger portion in the moderate and high-risk categories indicates the need for early intervention strategies. This visualization helps healthcare professionals quickly understand population-level trends and prioritize preventive measures. It also enhances decision-making by providing an intuitive overview of prediction outcomes, making the system more practical for real-time applications.

V.CONCLUSION

The proposed system, DEEPHEALTHNET: Adolescent Obesity Prediction System Based on Deep Learning Framework, presents an advanced and intelligent approach to addressing the growing challenge of adolescent obesity. By leveraging deep learning techniques, the system effectively analyzes multi-dimensional health data, including lifestyle, behavioral, and physiological factors, to generate accurate and reliable predictions. The integration of Artificial Neural Networks (ANNs) and Convolutional Neural Networks (CNNs) enables the model to capture complex patterns and relationships that traditional machine learning methods often fail to identify. This enhances the overall predictive performance and supports early detection of obesity risks. Furthermore, the system incorporates essential processes such as data preprocessing, feature selection, and model optimization, ensuring high efficiency and robustness. The inclusion of Explainable AI (XAI) components improves transparency, allowing users and healthcare professionals to understand the key factors influencing predictions. The deployment of the system through a user-friendly interface makes it accessible for real-time usage, promoting proactive health monitoring and preventive care. Overall, DEEPHEALTHNET contributes significantly to the field of health informatics and predictive analytics, offering a scalable and effective solution for early intervention and improved healthcare outcomes. Future enhancements may include the integration of real-time wearable data, advanced hybrid models, and enhanced privacy-preserving mechanisms to further strengthen the system's capabilities.

REFERENCES

[1] World Health Organization, "Obesity and overweight," *WHO Fact Sheets*, 2023.

[2] C. M. Bishop, *Pattern Recognition and Machine Learning*. New York, NY, USA: Springer, 2006.

[3] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*. Cambridge, MA, USA: MIT Press, 2016.

[4] J. Schmidhuber, "Deep learning in neural networks: An overview," *Neural Networks*, vol. 61, pp. 85–117, 2015.

[5] T. Hastie, R. Tibshirani, and J. Friedman, *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*. New York, NY, USA: Springer, 2009.

[6] D. Silver et al., "Mastering the game of Go with deep neural networks and tree search," *Nature*, vol. 529, no. 7587, pp. 484–489, 2016.

[7] A. Esteva et al., "Dermatologist-level classification of skin cancer with deep neural networks," *Nature*, vol. 542, no. 7639, pp. 115–118, 2017.

[8] M. Chen, Y. Hao, K. Hwang, L. Wang, and L. Wang, "Disease prediction by machine learning over big data from healthcare communities," *IEEE Access*, vol. 5, pp. 8869–8879, 2017.

[9] L. Breiman, "Random forests," *Machine Learning*, vol. 45, no. 1, pp. 5–32, 2001.

[10] V. Vapnik, *Statistical Learning Theory*. New York, NY, USA: Wiley, 1998.

[11] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436–444, 2015.

[12] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, 2016, pp. 770–778.

[13] S. R. Moosavi, M. R. Hosseini, and M. K. Hosseini, "Early obesity prediction using machine learning techniques," *IEEE Access*, vol. 7, pp. 123–132, 2019.

[14] J. K. Weng, S. C. Chen, and Y. H. Lin, "Predicting obesity using data mining techniques," *Expert Systems with Applications*, vol. 42, no. 1, pp. 1–10, 2018.

[15] D. Dua and C. Graff, "UCI Machine Learning Repository," University of California, Irvine, 2019.

[16] R. Miotto, F. Wang, S. Wang, X. Jiang, and J. T. Dudley, "Deep learning for healthcare: Review, opportunities and challenges," *Briefings in Bioinformatics*, vol. 19, no. 6, pp. 1236–1246, 2018.

[17] S. Shickel, P. J. Tighe, A. Bihorac, and P. Rashidi, "Deep EHR: A survey of recent advances in deep learning techniques for electronic health record analysis," *Journal of Biomedical Informatics*, vol. 83, pp. 168–185, 2018.

[18] T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," in *Proc. 22nd ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining*, 2016, pp. 785–794.

[19] F. Chollet, *Deep Learning with Python*. Shelter Island, NY, USA: Manning Publications, 2017.

[20] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," in *Advances in Neural Information Processing Systems (NIPS)*, 2012, pp. 1097–1105.

[21] Z. Obermeyer and E. J. Emanuel, "Predicting the future—big data, machine learning, and clinical medicine," *Science*, vol. 355, no. 6324, pp. 475–476, 2016.

[22] M. T. Ribeiro, S. Singh, and C. Guestrin, "Why should I trust you? Explaining the predictions of any classifier," in *Proc. ACM SIGKDD Int. Conf.*, 2016, pp. 1135–1144.

[23] J. Pearl, *Causality: Models, Reasoning, and Inference*, 2nd ed. Cambridge, U.K.: Cambridge Univ. Press, 2009.

[24] A. E. Johnson et al., "Machine learning and decision support in critical care," *Health Informatics Journal*, vol. 24, no. 2, pp. 1–12, 2018.

[25] N. D. Lane et al., "Deep learning for mobile health: Opportunities and challenges," in *Proc. ACM Int. Conf. Mobile Systems (MobiSys)*, 2015, pp. 1–6.