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ENHANCING TRUST IN OBESITY PREDICTION USING EXPLAINABLE STACKING MODELS

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ABSTRACT: The accuracy and reliability of obesity prediction are enhanced by the explainable stacking-based ensemble learning approach employed in this study, which integrates machine learning models. For the prevention of obesity, a global health concern, it is necessary to conduct an early and precise risk assessment. Decision trees, SVMs, and logistic regression comprise fundamental learners. Meta-learners enhance their performance by integrating predictions. Ensemble models are elucidated by Explainable AI (XAI). The decision patterns, feature contributions, and model outputs are all described by these methods. Interpretability and predictive power are enhanced by specifying BMI, nutrition, exercise, and lifestyle. The explainable layering model outperforms single classifiers and enhances the confidence and utility of clinical and public health. Experimental results support this assertion.

Keywords: *Obesity Risk Prediction, Ensemble Learning, Interpretable Machine Learning, LIME Explanations, Transparent AI, Healthcare Analytics,*

I. INTRODUCTION

Obesity on a global scale elevates the incidence of non-communicable diseases, including cardiovascular disease, metabolic syndromes, hypertension, and type 2 diabetes. Obesity is a result of genetics, lifestyle, environment, and socioeconomics. This renders early forecasting challenging, yet essential. The nonlinear and high-dimensional interactions between these components are frequently overlooked by conventional statistical methods. Machine learning technologies are widely used due to their ability to analyze intricate patterns in extensive health datasets and improve estimates of obesity risk.

Stacking models, which are ensemble learning methods, are more accurate than current machine learning. In layering, a meta-learner predicts from decision trees, SVMs, and neural networks. The use of layered design makes models more robust, broad, and less susceptible to overfitting. BMI, diet, exercise, demographics, and clinical indicators are predictors of obesity in stacking models.

Stacking models are controversial in healthcare due to their difficulty in comprehension, despite their ability to generate precise forecasts. Complex ensemble models are "black boxes." Individuals prioritize transparency, accountability, and ethics. Transparent predictive outcome derivations are essential for patients and healthcare providers. In order to establish trust, the reasoning processes of automated decision-support systems must be transparent and dependable. Consequently, even the most precise models may be rejected due to their lack of interpretability.

Transparent stacking frameworks are established by explanatory AI methodologies. Global and local predictions are elucidated by feature importance analysis, SHAP, LIME, and partial dependence plots. These methods assess the risk of obesity by considering socio-demographic, physiological, and behavioral factors. Physicians may expedite the process of making decisions based on evidence.

In order to establish the credibility of an obesity prediction system, it is imperative that we strike an equilibrium between interpretability and predictive performance. Health analytics accuracy, impartiality, transparency, and accountability are enhanced by explainable stacking models. These frameworks facilitate the responsible use of AI and the trust in intelligent healthcare decision-support systems by providing an explanation of the functionality and precision of the models.

II. LITERATURE SURVEY

Thamrin et al. (2021) Using national health survey data and machine learning, this study forecasts adult obesity. Demographic and behavioral evaluations are implemented for classifiers. The model accurately forecasts significant risks, such as inactivity and inadequate diet. The population screening is verified by the model. This investigation illustrates the application of machine learning to public health datasets.

Ferdowsy et al. (2021) Machine learning is employed to forecast obesity by analyzing physiological and behavioral data. Machine learning surpasses conventional methodologies. Numerous individuals emphasize the significance of exercise intensity and calories. This method is used to identify individuals who are at a high risk. The investigation investigates preventive healthcare analytics that are founded on machine learning.

Jeon, Lee & Oh (2022) The study employs machine learning and age-related risk factors to forecast obesity. Demography, health, and lifestyle are evaluated for individuals of all ages. The findings indicate that variables exhibit a significant degree of variation with age, which is consistent with individual risk modeling. Understanding is enhanced by an awareness of the value of characteristics. Life-stage-specific preventative care is necessary for the technique.

Kaur, Kumar & Gupta (2022) Scientists have suggested that artificial intelligence (AI) has the potential to identify obesity and develop customized nutrition programs. Health and lifestyle are classified by ML algorithms. Dietary guidelines mitigate risk. The investigations primarily verify the predictions. The primary objective of research is to modify behavior through the use of AI.

Fernandes et al. (2023) The investigation furnishes predictions regarding weight loss through artificial intelligence. Decisions regarding health care are enhanced by an understanding of machine learning algorithms. Prediction interpretation is facilitated by feature attribution. This instrument facilitates personalized treatment. The research indicates that XAI enhances patient-centered care.

Choudhuri (2023) In this investigation, a hybrid machine learning model is suggested for the assessment of obesity. Prediction is enhanced by numerous classifiers. Many models are

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suggested by performance evaluation. Ensemble approaches were determined to be effective in the investigation. The technique facilitates precise classification of obesity.

Wang (2024) This study investigates the assessment of obesity risk using lifestyle-based machine learning. Assessment of numerous classifiers. There are behaviors that significantly influence risk. The results suggest that machine learning-based screening is effective. Prevention that is informed by data is encouraged by the investigation.

Özkurt (2024) The work employs basic artificial intelligence to evaluate the risk of obesity. The predicted results are demonstrated through the analysis of the machine learning model. Computer projections are dependable and transparent. Lifestyle adjustments are recommended by the results. According to this investigation, health analytics necessitates clarification.

Görmez et al. (2025) An interpretable obesity trend machine learning platform is established by SHAP and LIME. Our models are evaluated through the use of physiological and activity data. The primary predictions of each individual are revealed by explainability methodologies. Clinic procedures are straightforward to comprehend and monitor. Customization of risk communication is substantiated by the results.

Ganie, Reddy & Rege (2025) Obesity in various demographics could be predicted by ensemble learning systems that utilize real-time data from the participants of this study. Ensembles enhance the precision of each category. Lifestyle and behavior are prioritized in the explainability evaluation. This approach facilitates the rapid and accurate organization of hazards. Interpretable ensemble models are validated by this investigation.

III. EXPERIMENTAL DESIGN

DATASET COLLECTION

Data on demographics, lifestyle, genetics, and physical health are arranged in obesity risk prediction models. Both direct and indirect causes of obesity are included in the dataset. Weight gain and metabolic imbalance are noted for each attribute. Through ensemble learning, data is effectively identified.

Demographic Variables

Age: Age has an impact on fat content, distribution, and metabolism. Because of their slower metabolisms, older people burn fewer calories. Fat and muscle are affected by endocrine changes that occur during puberty, adulthood, and aging. The model identifies patterns in obesity and age-related risk.

Gender: Gender differences exist in metabolism, hormone balance, and fat storage. Both male and female obesity are influenced by testosterone and estrogen. Exercise and diet may change depending on a person's gender. The model takes gender-specific behavior and biology into consideration.

Anthropometric Indicator

Body Mass Index (BMI): BMI is a measure of adiposity. To compute, divide the weight in kilograms by the square of the height in meters (kg/m^2). People are classified as underweight, normal, overweight, and obese based on their BMI. Obesity is defined and predicted by BMI.

Genetic Factor

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Family History of Obesity: Obesity is significantly influenced by genetics. Family obesity raises the risk of obesity because of metabolic and environmental variables.

Lifestyle & Behavioral Factors

Physical Activity Level: Activity is necessary for both energy expenditure and weight loss. This stands for the frequency, length, and intensity of workouts. While inactivity increases the risk of obesity, exercise increases metabolism and burns fat. In order to explain how exercise inhibits weight gain, this variable should be included in the model.

Dietary Habits: Diet affects the absorption of calories and nutrients. Eat a lot of fruits, vegetables, fast meals, snacks, and high-calorie items. Obesity is caused by excessive eating of sugar and fat. The approach uses eating patterns to identify nutritional aspects associated with obesity.

Daily Water Intake: Hydration promotes hunger, metabolism, and digestion. Water consumption may improve metabolism and reduce caloric expenditure. It shows the average amount of water consumed each day. Alcohol and weight control can be examined using this strategy.

Smoking and Alcohol Consumption: Obesity is indirectly caused by drinking and smoking. Alcohol with a lot of calories produces belly obesity. Smoking affects energy and hunger. The model might investigate the indirect effects of these habits on obesity.

Screen Time and Sedentary Behavior: Long-term computer usage, mobile gadgets, and television promote sitting and decrease activity. Sitting for extended periods of time might reduce calorie expenditure and lead to overeating. Inactivity leads to fat and obesity.

Meal Frequency and Snacking Behavior: Meal and snack frequency determines daily caloric intake. Frequent meals or high-calorie snacks can lead to energy imbalance and weight gain. This feature allows the model to track eating habits and obesity.

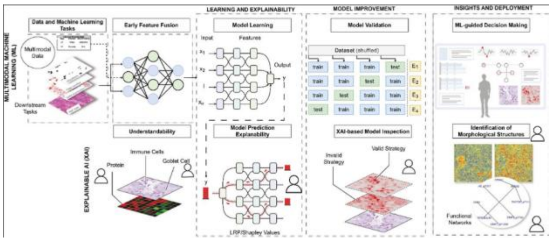

Fig 1: Multimodal Machine Learning and Explainable AI Framework

IV. RESULTS

Fig 4.1: Login Page

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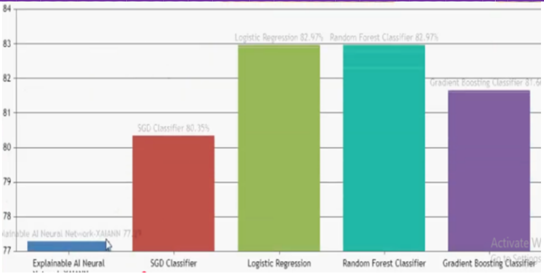

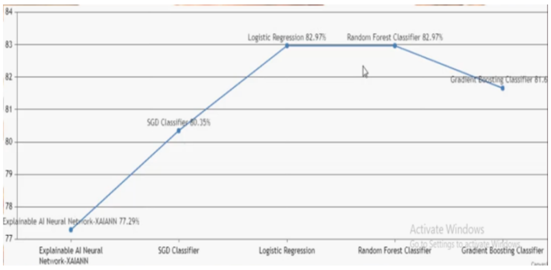

Fig 4.2: Comparison site for model accuracy

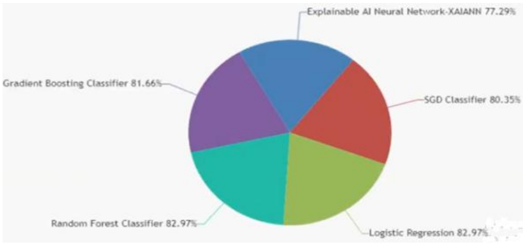

Fig 4.3: Trend page for classifier accuracy

Fig 4.4: Distribution of Classifier Accuracy.png

Fig 4.5: User Registration Page

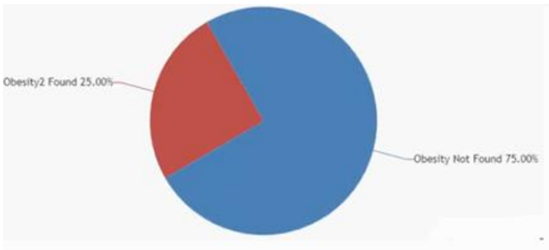

Fig 4.6: Obesity Prediction Pie Chart

V. CONCLUSION

Last but not least, effective obesity prediction algorithms need to be straightforward and precise. Explainable stacking models assist students in striking a balance between accountability and performance. These models explain how BMI, lifestyle, food, and activity levels impact forecasts, which enhances clinician trust, ethical AI use in healthcare, and decision-making. Explainable stacking frameworks reduce the "black-box" nature of

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traditional ensemble techniques and promote rule compliance, user confidence, and the adoption of preventative healthcare systems.

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