# Deep Learning in Adolescent Obesity Prevention : A path to Health

*A Project Report submitted in the partial fulfillment of*

*the Requirements for the award of the degree*

**BACHELOR OF TECHNOLOGY**

**IN**

**COMPUTER SCIENCE AND ENGINEERING**

Submitted by

**Srilatha Amireddy (21471A0503)**

**Chinni Indravati (21471A0527)**

**Sripati Chandana (21471A0562)**

Under the esteemed guidance of

G.Saranya, M.Tech.,(Ph.D)

Asst. Professor

**DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING**

NARASARAOPETA ENGINEERING COLLEGE: NARASAROPET

(AUTONOMOUS)

Accredited by NAAC with A+ Grade and NBA under Tyre -1

NIRF rank in the band of 201-300 and an ISO 9001:2015 Certified

Approved by AICTE, New Delhi, Permanently Affiliated to JNTUK, Kakinada

KOTAPPAKONDA ROAD, YALAMANDA VILLAGE, NARASARAOPET- 522601

2024-2025

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# CERTIFICATE

**This is to certify that the project that is entitled with the name "**Deep Learning in Adolescent Obesity Prevention : A Path to Health**" is a bonafide work done by the team Srilatha Amireddy (21471A0503), Chinni Indravati (21471A0527), Sripati Chandana (21471A0562)** in partial fulfillment of the requirements for the award of the degree of BACHELOR OF TECHNOLOGY in the Department of COMPUTER SCIENCE AND ENGINEERING during 2024-2025.

PROJECT GUIDE

**G.Saranya, M.Tech..,(Ph.D)**

**Asst. Professor**

PROJECT CO-ORDINATOR

**D.Venakata Reddy., M.Tech.(Ph.D), .**

**Asst. Professor**

HEAD OF THE DEPARTMENT

**Dr. S. N. Tirumala Rao, M.Tech., Ph.D.,**

**Professor & HOD**

EXTERNAL EXAMINER

# DECLARATION

We declare that this project work titled " DEEP LEARNING IN ADOLESCENT OBESITY PREVENTION : A PATH TO HEALTH " is composed by ourselves that the work contain here is our own except where explicitly stated otherwise in the text and that this work has been submitted for any other degree or professional qualification except as specified.

Srilatha Amireddy (21471A0503)

Chinni Indravati (21471A0527)

Sripati Chandana (21471A0562)

# ACKNOWLEDGEMENT

We wish to express my thanks to carious personalities who are responsible for the completion of the project. We are extremely thankful to our beloved chairman sri **M. V.Koteswara Rao**, **B.Sc.**, who took keen interest in us in every effort throughout thiscourse. We owe out sincere gratitude to our beloved principal **Dr. S. Venkateswarlu, Ph.D.**, for showing his kind attention and valuable guidance throughout the course.

We express our deep felt gratitude towards **Dr. S. N.Tirumala Rao,M.Tech.,Ph.D.,** HOD of CSE department and also to our guide **G.Sarnaya,M.Tech.(Ph.D),** of CSE department whose valuable guidance and unstinting encouragement enable us to accomplish our project successfully in time.

We extend our sincere thanks towards **D.Venkata Reddy**, **M.Tech.(Ph.D).,** Associate professor & Project coordinator of the project for extending her encouragement. Their profound knowledge and willingness have been a constant sourceof inspiration for us throughout this project work.

We extend our sincere thanks to all other teaching and non-teaching staff to department for their cooperation and encouragement during our B.Tech degree.

We have no words to acknowledge the warm affection, constant inspiration and encouragement that we received from our parents.

We affectionately acknowledge the encouragement received from our friends and those who involved in giving valuable suggestions had clarifying out doubts which hadreally helped us in successfully completing our project.

By

**Srilatha Amireddy (21471A0503)**

**Chinni Indravati (21471A0527)**

**Sripati Chandana (21471A0562)**

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The graduates of the programme are able to:

**PEO1:** Apply the knowledge of Mathematics, Science and Engineering fundamentals to identify and solve Computer Science and Engineering problems.

**PEO2:** Use various software tools and technologies to solve problems related to academia, industry and society.

**PEO3:** Work with ethical and moral values in the multi-disciplinary teams and can communicate effectively among team members with continuous learning.

**PEO4:** Pursue higher studies and develop their career in software industry.

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**Design/development of solutions:** Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.

**Conduct investigations of complex problems:** Use research-based knowledge and research methods including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.

**Modern tool usage:** Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modeling to complex engineering activities with an understanding of the limitations.

**The engineer and society:** Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal and cultural issues and the consequent responsibilities relevant to the professional engineering practice.

**Environment and sustainability:** Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for sustainable development.

**Ethics:** Apply ethical principles and commit to professional ethics and responsibilitiesand norms of the engineering practice.

**Individual and team work**: Function effectively as an individual, and as a member orleader in diverse teams, and in multidisciplinary settings.

**Communication**: Communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.

**Project management and finance**: Demonstrate knowledge and understanding of theengineering and management principles and apply these to one's own work, as a member and leader in a team, to manage projects and in multidisciplinary environments.

**Life-long learning**: Recognize the need for, and have the preparation and ability to engage in independent and life-long learning in the broadest context of technological change.

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## Project Course Outcomes (CO'S):

**CO421.1:** Analyze the System of Examinations and identify the problem.

**CO421.2:** Identify and classify the requirements.**CO421.3:** Review the Related Literature

**CO421.4:** Design and Modularize the project

**CO421.5:** Construct, Integrate, Test and Implement the Project.

**CO421.6:** Prepare the project Documentation and present the Report using appropriate method.

## Course Outcomes – Program Outcomes mapping

| | PO1 | PO2 | PO3 | PO4 | PO5 | PO6 | PO7 | PO8 | PO9 | PO10 | PO11 | PO12 | PSO1 | PSO2 | PSO3 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **C421.1** | | √ | | | | | | | | | | | √ | | |
| **C421.2** | √ | | √ | | √ | | | | | | | | √ | | |
| **C421.3** | | | | √ | | √ | √ | √ | | | | | √ | | |
| **C421.4** | | | √ | | | √ | √ | √ | | | | | √ | √ | |
| **C421.5** | | | | | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ |
| **C421.6** | | | | | | | | | √ | √ | √ | | √ | √ | |

## Course Outcomes – Program Outcome correlation

| | PO1 | PO2 | PO3 | PO4 | PO5 | PO6 | PO7 | PO8 | PO9 | PO10 | PO11 | PO12 | PSO1 | PSO2 | PSO3 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **C421.1** | 2 | 3 | | | | | | | | | | | 2 | | |
| **C421.2** | | | 2 | | 3 | | | | | | | | 2 | | |
| **C421.3** | | | | 2 | | 2 | 3 | 3 | | | | | 2 | | |
| **C421.4** | | | 2 | | | 1 | 1 | 2 | | | | | 3 | 2 | |
| **C421.5** | | | | | 3 | 3 | 3 | 2 | 3 | 2 | 2 | 1 | 3 | 2 | 1 |
| **C421.6** | | | | | | | | | 3 | 2 | 1 | | 2 | 3 | |

**Note: The values in the above table represent the level of correlation between CO's and PO's:**

1. Low level
2. Medium level
3. High level

## Project mapping with various courses of Curriculum with Attained PO's:

| Name of the course from which principles are applied in this project | Description of the device | Attained PO |
|---|---|---|
| C2204.2, C22L3.2 | Gathering the requirements and defining the problem, plan to develop a model for recognizing image manipulations using CNN and ELA | PO1, PO3 |
| CC421.1, C2204.3, C22L3.2 | Each and every requirement is critically analyzed, the process model is identified | PO2, PO3 |
| CC421.2, C2204.2, C22L3.3 | Logical design is done by using the unified modelling language which involves individual team work | PO3, PO5, PO9 |
| CC421.3, C2204.3, C22L3.2 | Each and every module is tested, integrated, and evaluated in our project | PO1, PO5 |
| CC421.4, C2204.4, C22L3.2 | Documentation is done by all our four members in the form of a group | PO10 |
| CC421.5, C2204.2, C22L3.3 | Each and every phase of the work in group is presented periodically | PO10, PO11 |
| C2202.2, C2203.3, C1206.3, C3204.3, C4110.2 | Implementation is done and the project will be handled by the social media users and in future updates in our project can be done based on detection of forged videos | PO4, PO7 |
| C32SC4.3 | The physical design includes website to check whether an image is real or fake | PO5, PO6 |

# ABSTRACT

This research highlights the importance of employing advanced machine learning techniques to address the complexities of adolescent health. By focusing on individual level interventions and incorporating a variety of health factors, the study aims to improve the management of adolescent obesity and promote healthier lifestyle choices. The findings underscore the necessity for targeted prevention strategies that consider gender differences, ultimately contributing to enhanced health outcomes for the younger population. The DeepHealthNet model incorporates critical variables such as height, weight, caloric intake, and physical activity levels to enhance prediction accuracy. The model achieved an overall accuracy of 0.9437, with gender-specific accuracies of 0.9561 for boys and 0.9423 for girls, demonstrating its effectiveness in identifying.

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# 1. INTRODUCTION

## 1.1 Introduction

Child and adolescent obesity has emerged as one of the most pressing public health challenges globally. The World Health Organization (WHO) reports a staggering increase in the number of overweight or obese children and adolescents aged five to nineteen, rising from 11 million in 1975 to 340 million in 2020. This alarming trend not only poses immediate health risks but also sets the stage for long-term complications, as obesity during adolescence often leads to obesity in adulthood[1].The associated health risks, including diabetes, cardiovascular diseases, and mental health issues, underscore the urgent need for effective intervention strategies.

Despite the growing recognition of adolescent obesity as a critical issue, current research often falls short in addressing the multifaceted determinants of health that contribute to this epidemic. Traditional methods of predicting obesity risk have demonstrated relatively low accuracy and efficiency, highlighting the necessity for innovative approaches. The increasing complexity of adolescent health necessitates the development of advanced predictive models that can accurately assess obesity risk and inform targeted interventions.[2]

| CHARACTERISTIC | CHILDREN'S WEIGHT STATUS | | |
|---|---|---|---|
| | % Normal (*N* = 218) | % Overweight (*N* = 56) | % Obese (*N* = 47) |
| *Maternal Early Pregnancy Weight** | | | |
| Underweight | 79 (23) | 21 (6) | 0 (0) |
| Normal weight | 73 (111) | 20 (30) | 8 (12) |
| Overweight | 72 (42) | 17 (10) | 10 (6) |
| Obese | 52 (42) | 12 (10) | 36 (29) |
| *Infant Birth Weight* | | | |
| < 3 kg | 67 (22) | 15 (5) | 18 (6) |
| ≥ 3 < 3.5 kg | 78 (84) | 12 (13) | 10 (11) |
| ≥ 3.5 < 4 kg | 63 (71) | 21 (23) | 16 (18) |
| ≥ 4 kg | 60 (41) | 22 (15) | 18 (12) |
| *Gestational Weight Gain* | | | |
| Inadequate | 68 (42) | 16 (10) | 16 (10) |
| Appropriate | 71 (92) | 18 (23) | 11 (14) |
| Excessive | 65 (84) | 18 (23) | 18 (23) |
| *Maternal Weight Change from 1 to 2 Years Postpartum (N = 245)* | | | |
| Decreased ≥ 5 pounds | 73 (49) | 8 (5) | 19 (13) |
| Stayed within 5 pounds | 66 (78) | 23 (27) | 12 (14) |
| Increased ≥ 5 pounds | 70 (41) | 15 (9) | 15 (9) |

**Fig 1.1 Proportion of the Children**

This study aims to address these gaps by employing a deep learning model, referred to as DeepHealthNet, to predict obesity risk among adolescents. By analyzing cross-sectional data from a diverse sample of boys and girls, the research seeks to uncover the relationship between Body Mass Index (BMI) and Waist Circumference (WC) while considering gender differences in obesity risk factors.[3] The findings from this study are expected to contribute valuable insights into the design of effective obesity prevention strategies tailored to the unique needs of adolescents.

Obesity affects male and female adolescents differently due to biological, hormonal, and behavioral differences**.** Research has shown that boys are more likely to accumulate visceral fat, whereas girls tend to store more subcutaneous fat, leading to variations in obesity-related health risks. Additionally, dietary preferences, metabolic rates, and physical activity levels vary between genders, influencing weight gain patterns.[4][5]A gender-sensitive approach to obesity prediction **is** therefore essential to ensure more accurate risk assessments and tailored intervention strategies**.**

Deep learning models can be trained to recognize gender-specific obesity risk factors, enabling healthcare professionals to design targeted weight management programs. For example, an AI model can recommend strength training and protein-rich diets for boys with a high obesity risk, while suggesting cardio-based exercises and balanced macronutrient intake for girls based on their unique metabolic needs.

Beyond improving predictive models, this research underscores the importance of empowering adolescents to take an active role in their healthcare decisions. By focusing on individual-level interventions that account for a wide range of health determinants, the study promotes personalized obesity management strategies. Encouraging healthy lifestyle choices through nutritional education, physical activity programs, and mental health support can foster long-term behavioral changes, ultimately reducing obesity rates among adolescents.[6]

The broader goal of this study is to lay a foundation for future advancements in adolescent healthcare, particularly in the early detection and prevention of obesity. By integrating artificial intelligence (AI) into public health strategies, the research paves the way for personalized, data driven interventions that can significantly improve the health outcomes of younger generations. As childhood obesity continues to rise at an alarming rate, such innovative approaches are crucial in reversing this trend and ensuring a healthier future.

In addition to enhancing predictive accuracy, this research emphasizes the importance of involving adolescents in their healthcare decisions. By focusing on individual-level interventions that consider various health factors, the study aims to improve the management of adolescent obesity and promote healthier lifestyles. Ultimately, the goal is to provide a foundation for future advancements in adolescent health care, facilitating early detection and personalized interventions that can significantly impact the health outcomes of the younger generation[7][8].

The prevalence of boosting techniques in obesity prediction has gained momentum in response to the increasing complexity of health data and the need for accurate risk assessment[2]. Boosting algorithms, such as AdaBoost and Gradient Boosting, are widely adopted in this domain for their ability to enhance prediction accuracy and reduce false positive rates, significantly outperforming traditional single-model approaches. These techniques allow for the integration of multiple weak learners to create a strong predictive model, which is particularly beneficial in identifying subtle patterns associated with obesity risk.

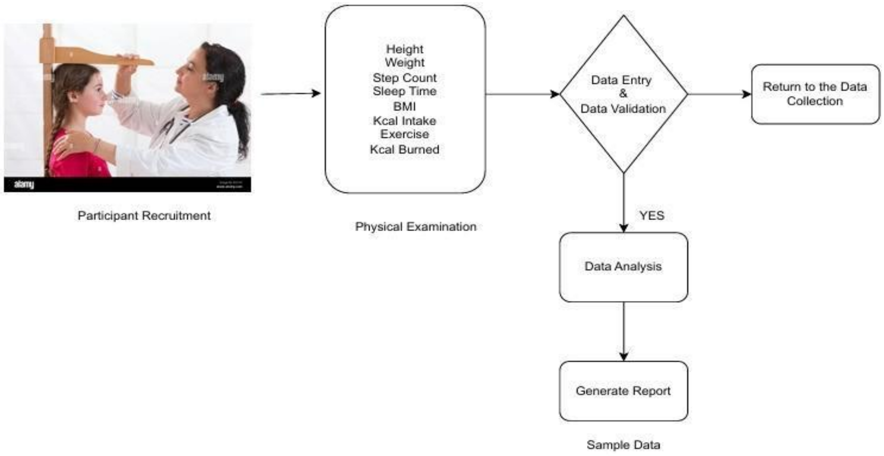



**Fig : 1.2 Physical Data Collection**

The image depicts a flowchart outlining the process of data collection and validation in a medical or health-related study, specifically focusing on physical examination and data analysis.

The process begins with "Participant Recruitment," represented by an image of a doctor measuring the height of a young girl. This step signifies the initial stage where participants are recruited for a study, likely related to health or medical research.

Next, the flowchart leads to a box labeled "Physical Examination," listing various health parameters such as height, step count, sleep time, calories burned, and BMI. This indicates that participants undergo a physical examination to gather relevant health data.

The next step in the flowchart is "Data Entry & Data Validation," represented as a decision-making diamond. Here, the collected information is entered into a system and checked for accuracy. If any data inconsistencies or errors are found, the process loops back to "Return to the Data Collection" stage for corrections or re-evaluation.

If the data passes validation, it proceeds to the "Data Analysis" stage, where it is analyzed for insights. The final step in the flowchart is "Generate Report," which suggests that the validated data is compiled into a report, likely summarizing key findings or insights derived from the data.

Additionally, the application of two-level ensemble learning has become prominent, enabling a more comprehensive analysis of health-related data by integrating various predictive models. This approach effectively captures diverse factors influencing obesity, such as dietary habits, physical activity, and demographic variables, leading to improved prediction capabilities

Furthermore, knowledge distillation is emerging as a popular strategy for deploying lightweight models in obesity prediction applications. This technique allows for the transfer of knowledge from complex ensemble models to smaller, more efficient models, enabling real-time applications without sacrificing performance.[9] By addressing computational constraints while maintaining effective prediction accuracy, organizations can implement these models in practical settings, such as mobile health applications or community health programs.

Overall, the integration of these advanced boosting techniques reflects a growing trend in obesity prediction, emphasizing the need for robust and efficient solutions to address the rising prevalence of obesity among adolescents. By leveraging these methodologies, the proposed system aims to provide accurate and timely predictions, ultimately contributing to effective prevention and intervention strategies.

Deep learning plays a crucial role in enhancing obesity prediction systems by automatically extracting complex features from large and diverse health datasets. This capability allows for the accurate identification of subtle patterns and risk factors associated with obesity that traditional methods may overlook[10].When integrated with boosting techniques, deep learning models act as powerful base learners, significantly improving overall prediction performance. By leveraging their ability to learn intricate representations of health-related data such as dietary habits, physical activity levels, and demographic information these models enhance the accuracy of obesity risk assessments, making them more reliable for identifying at-risk individuals.

Furthermore, the two-level ensemble approach benefits from deep learning's robustness by integrating multiple deep models, which captures diverse behaviors and anomalies in health data. This comprehensive analysis addresses the multifaceted nature of obesity, leading to improved prediction capabilities. Additionally, knowledge distillation enables the compression of sophisticated deep models into smaller, efficient versions without significant loss of accuracy, facilitating real-time applications in mobile health technologies and community health initiatives.

## 2. LITERATURE SURVEY

Adolescent obesity has emerged as a critical public health issue globally, with alarming trends indicating a significant increase in prevalence over recent decades. According to the World Health Organization (WHO), the number of overweight or obese children and adolescents aged five to nineteen years surged from 11 million in 1975 to 340 million in 2020. This dramatic rise underscores the urgent need for effective interventions, as obesity during adolescence often leads to obesity in adulthood, increasing the risk of severe health complications and diminishing quality of life. The implications of these statistics are profound, highlighting the necessity for targeted strategies to combat obesity among youth and improve their long-term health outcomes[11].

Research indicates that gender differences significantly influence the prevalence and risk factors associated with adolescent obesity. Studies have shown that boys and girls exhibit different patterns of obesity, necessitating a gender-sensitive approach to prevention and intervention strategies. For instance, the predictive modeling conducted in this study revealed that boys demonstrated greater variance in obesity risk factors compared to girls, with the model achieving an accuracy of 0.9561 for boys and 0.9423 for girls. These findings emphasize the importance of tailoring interventions to address the unique needs of each gender, thereby enhancing the effectiveness of obesity prevention programs[12].

The complexity of adolescent obesity is further compounded by various contributing factors, including socioeconomic status, dietary habits, and lifestyle choices. The increasing availability of high-calorie, low-nutrient foods, combined with sedentary behaviors such as excessive screen time, has exacerbated the obesity epidemic. Additionally, environmental factors, such as access to recreational spaces and healthy food options, play a crucial role in shaping adolescents' health behaviors[13].Understanding these multifaceted influences is essential for developing comprehensive strategies to mitigate obesity risk among youth.

Recent advancements in deep learning and health data analytics have opened new avenues for predicting and managing adolescent obesity. By leveraging large datasets, including electronic health records and lifestyle information, deep learning models can identify complex patterns and predictors of obesity with high accuracy. These models are capable of processing non-linear relationships among variables, providing deeper insights into the factors contributing to obesity. Furthermore, they enable the development of personalized intervention strategies by predicting individual risk levels based on a comprehensive analysis of health data. This individualized approach not only enhances the effectiveness of obesity prevention programs but also empowers adolescents to take proactive steps in managing their health[15][16].

Obesity has become a pressing health concern globally, prompting researchers to explore various methodologies for its prediction, prevention, and management. Several studies have contributed to this domain by integrating machine learning, deep learning, IoT, and behavioral interventions. The work by multiple authors on "Obesity Prediction with EHR Data" focuses on utilizing electronic health records (EHR) for predictive modeling, enhancing early detection methods. Similarly, the "DeepHealthNet Framework" incorporates deep learning techniques, improving accuracy over traditional statistical models. In contrast, the study "Deep Learning in Obesity Prediction" extends the previous approaches by integrating neural networks, providing better feature extraction and classification capabilities. These advancements indicate a shift from conventional predictive models to AI-driven frameworks that enhance diagnostic efficiency[16].

Expanding beyond AI-based methodologies, "Global Obesity Trends" by various researchers examines obesity's prevalence worldwide, highlighting changes in dietary habits, sedentary lifestyles, and socioeconomic influences. Further, the "Predictive Modeling for Adolescent Obesity" refines previous approaches by targeting younger demographics, integrating more age-specific behavioral and genetic factors. Meanwhile, the "Sleep and Obesity in Children and Adolescents: A Systematic Review" bridges the gap between lifestyle factors and obesity, identifying how irregular sleep patterns contribute to weight gain and metabolic disorders. These studies emphasize the need for comprehensive health strategies incorporating lifestyle modifications alongside predictive technologies[17].

Technological interventions in obesity management have also gained traction. The study on "A Patient-Specific Single Sensor IoT-Based Wearable System" introduces a real-time monitoring approach, enhancing patient-specific health tracking. This development marks a significant change from generalized obesity assessments to personalized health monitoring, offering tailored recommendations. Similarly, "Promoting Obesity Prevention and Healthy Habits in Schools" focuses on behavioral interventions at an institutional level, addressing obesity through structured school-based programs. Unlike previous studies that emphasize medical and technological solutions, this work underlines the importance of educational and policy-driven initiatives[18].

The capabilities of machine learning by implementing Deep Neural Networks (DNNs) to enhance obesity prediction. Previous studies relied on traditional statistical models, but this paper explores how deep learning's ability to self-learn from vast datasets can yield more precise outcomes. The model outperforms conventional classifiers like Decision Trees and Support Vector Machines (SVMs) by effectively handling non-linear relationships between multiple obesity risk factors, such as genetic predisposition, dietary habits, and physical activity levels. The paper emphasizes how deep learning provides a scalable and adaptive solution to obesity prediction, setting a benchmark for future AI-driven health assessments[19].

The focus to adolescent obesity, exploring how predictive modeling can assess weight gain risks among teenagers. The study differs from other obesity prediction research by incorporating behavioral, genetic, and environmental factors unique to adolescents. The authors employ Random Forest and Gradient Boosting algorithms to analyze key parameters such as screen time, sleep quality, dietary intake, and parental obesity history. A significant contribution of this paper is the proposal of personalized intervention strategies unlike generalized obesity models, this study suggests individualized health recommendations for adolescents at risk[18].

The role of educational institutions in combating obesity. Unlike predictive modeling studies, this paper focuses on prevention rather than diagnosis. The authors propose school-based intervention programs that promote physical activity, nutritional awareness, and mental well-being among students. The paper highlights case studies of successful school programs and emphasizes multi disciplinary collaboration between educators, nutritionists, and policymakers. The study suggests that integrating structured health curricula in schools can have long-term benefits in reducing childhood and adolescent obesity rates[19].

The correlation between sleep patterns and obesity in young individuals. Unlike previous studies that primarily focus on dietary and genetic factors, this research highlights sleep deprivation as a critical yet often overlooked risk factor for obesity. The systematic review consolidates findings from multiple studies and reveals that insufficient sleep leads to metabolic dysregulation, increased appetite, and unhealthy eating habits, all of which contribute to weight gain. The study emphasizes the importance of sleep quality in obesity prevention programs and suggests interventions such as sleep hygiene education and school-based awareness programs.

In the realm of deep learning optimization, "Generalized Cross-Entropy Loss for Training Deep Neural Networks" proposes improvements in model training by reducing biases in weight updates, enhancing accuracy in obesity prediction models. This study advances earlier deep learning applications by refining loss functions, ensuring robustness across diverse datasets. Collectively, these research contributions demonstrate a progressive shift from basic statistical models to AI-driven solutions, IoT-based health tracking, and policy interventions. By comparing these studies, it is evident that obesity research is evolving through interdisciplinary collaborations, incorporating machine learning, lifestyle studies, and behavioral sciences to develop more effective prevention and intervention strategies.

These studies collectively represent significant advancements in obesity prediction, monitoring, and prevention. While some papers focus on data-driven prediction models (such as EHR-based obesity prediction, DeepHealthNet, and Deep Learning models), others emphasize real-time monitoring through IoT devices and behavioral analysis (such as wearable sensor-based monitoring and sleep-obesity correlation). Furthermore, global studies like obesity trend analysis and school-based intervention programs provide policy-level insights into obesity management.

A major improvement across these studies is the integration of artificial intelligence (AI) and IoT technologies in healthcare, which significantly enhances obesity monitoring and risk prediction. Additionally, these papers highlight the growing interdisciplinary approach where machine learning, behavioral science, and healthcare policies merge to develop holistic obesity management strategies.

# 3. SYSTEM ANALYSIS

## 3.1 EXISTING SYSTEM:

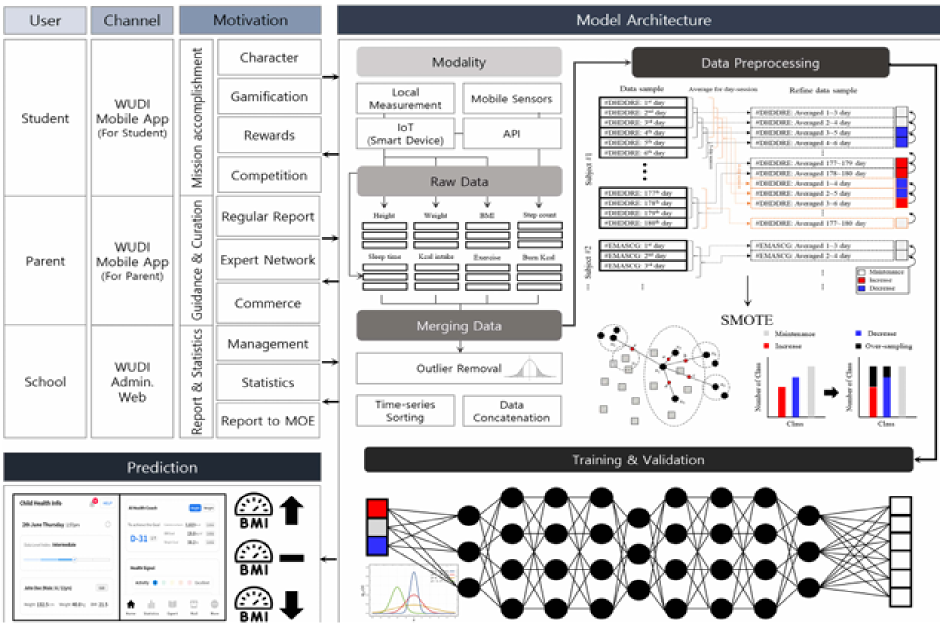



**Fig 3.1.1 Flow chart of existing system**

The diagram illustrates an AI-driven obesity prediction system integrating mobile applications, IoT devices, and deep learning. It begins by categorizing users into three groups: students, parents, and schools, each interacting with the system through dedicated platforms. Students engage with the WUDI Mobile App, which incorporates gamification, rewards, and competition to encourage healthy habits. Parents use a separate WUDI Mobile App to monitor their child's health, receive expert guidance, and access statistical reports. Schools utilize the WUDI Admin Web for statistical analysis and reporting to the Ministry of Education[4]. The model architecture follows a structured pipeline where data is collected through local measurements, mobile sensors, IoT devices, and APIs. This raw data, which includes metrics like height, weight, BMI, sleep patterns, and exercise habits, undergoes preprocessing steps such as outlier removal, time-series sorting, and data merging. To address data imbalance, the SMOTE (Synthetic Minority Over-sampling Technique) method is applied, ensuring the deep learning model receives a well-balanced dataset[9][11]. The processed data is then used to train a neural network, optimizing prediction accuracy through multiple layers and learning techniques. Once validated, the model provides real-time BMI predictions displayed in the WUDI Mobile App, offering personalized insights and tracking progress over time. [1].

Intrusion Detection Systems (IDS) employ various techniques to detect unauthorized access or suspicious activity. Signature-based detection compares network activity against known attack patterns, effectively identifying familiar threats but struggling with new ones. In contrast, anomaly-based detection establishes a baseline of normal behavior, flagging deviations as potential threats, which allows it to detect unknown attacks but can lead to more false positives. Heuristic and behavioral-based methods analyze user and network actions to identify unusual behavior patterns. Increasingly, machine learning (ML) techniques including supervised and unsupervised models are leveraged to dynamically classify and adapt to new attack patterns. Advanced IDS often use hybrid detection, combining multiple methods, such as ML with signature-based approaches, enhancing accuracy while reducing false positives. Additionally, reputation-based detectionassesses traffic based on the history of IP sources, adding a layer of quick threat identification. Together, these techniques provide a robust, adaptive defense against evolving cyber threats.

## 3.2 DISADVANTAGES OF EXISTING SYSTEM

1. **Data Privacy and Security Risks**

One of the most pressing concerns associated with an obesity prediction system is data privacy. The system collects and processes sensitive health-related information, including weight, BMI, activity levels, and personal habits. This data, if not handled securely, can be vulnerable to breaches, unauthorized access, or misuse. Cyberattacks and data leaks could expose users to privacy violations, identity theft, or potential discrimination. Compliance with health data regulations such as HIPAA (Health Insurance Portability and Accountability Act) or GDPR is essential to maintain user trust and protect their sensitive information.

**2. Accuracy and Bias in Prediction Models**

The effectiveness of an obesity prediction system depends on the accuracy of its machine learning models. Bias in training data can lead to incorrect or unfair predictions, disproportionately affecting certain demographic groups. If the dataset used for training is not diverse, the model might generate biased results, which can misinform users or even lead to inappropriate health recommendations. Factors such as genetic predisposition, socioeconomic background, and lifestyle choices are complex and not always adequately represented in datasets, potentially leading to inaccuracies in predicting obesity risk.

**3. Accessibility and Digital Divide**

The system is highly dependent on digital devices such as smartphones, wearables, and internet connectivity. However, not all users have access to such technology, leading to disparities in healthcare. Lower-income families may not be able to afford wearable devices or smartphones required for real-time tracking and analysis. Additionally, elderly individuals or those with limited digital literacy may find it challenging to use the system effectively, limiting its reach to only a specific segment of the population.

**4. User Compliance and Engagement**

The success of any digital health platform, including obesity prediction systems, depends on user compliance. Many users may not be comfortable consistently tracking their weight, diet, and lifestyle habits due to forgetfulness, lack of motivation, or psychological factors. If users do not engage with the system consistently, the accuracy and reliability of predictions may decline, reducing its effectiveness in combating obesity.

**5. Computational and Resource Intensiveness**

Deep learning models require significant computational resources, which can be a challenge for real-time analysis, especially in low-resource settings. The system may demand powerful hardware or cloud-based computing, which may increase operational costs and present affordability issues for users or healthcare providers.

**6. Ethical Concerns and Social Stigmatization**

The implementation of obesity prediction systems might inadvertently contribute to stigmatization. Labelling individuals as "high risk" for obesity could lead to self-esteem issues, anxiety, or even discrimination. It is crucial to handle such data sensitively and provide recommendations that encourage positive behavioral changes without fostering a culture of shame.

## 3.3. PROPOSED SYSTEM

A two-level ensemble learning approach is combined with knowledge distillation techniques to enhance the efficiency and accuracy of network intrusion detection. At the first level, multiple base classifiers are deployed to capture diverse attack patterns, leveraging complementary strengths to maximize detection performance. These base classifiers' outputs are then aggregated through a secondary ensemble layer, which intelligently weighs the results to minimize false positives and detect sophisticated intrusion types. Knowledge distillation further refines this ensemble by transferring knowledge from a high-capacity teacher model to a smaller, resource-efficient student model. This enables high detection accuracy while reducing computational demands, making the system viable for real-time monitoring on large-scale networks. Through this combination, the proposed system achieves robust, adaptive intrusion detection, capable of identifying both known and emerging threats across complex network environments.

**Advantages:**

1. Improved Detection Accuracy
2. Enhanced Adaptability to New Threats
3. Reduced False Positives
4. Efficient Resource Utilization
5. Real-Time Detection Capabilities
6. Scalability for Large-Scale Networks
7. Low Computational Overhead
8. Effective Knowledge Transfer Through Distillation

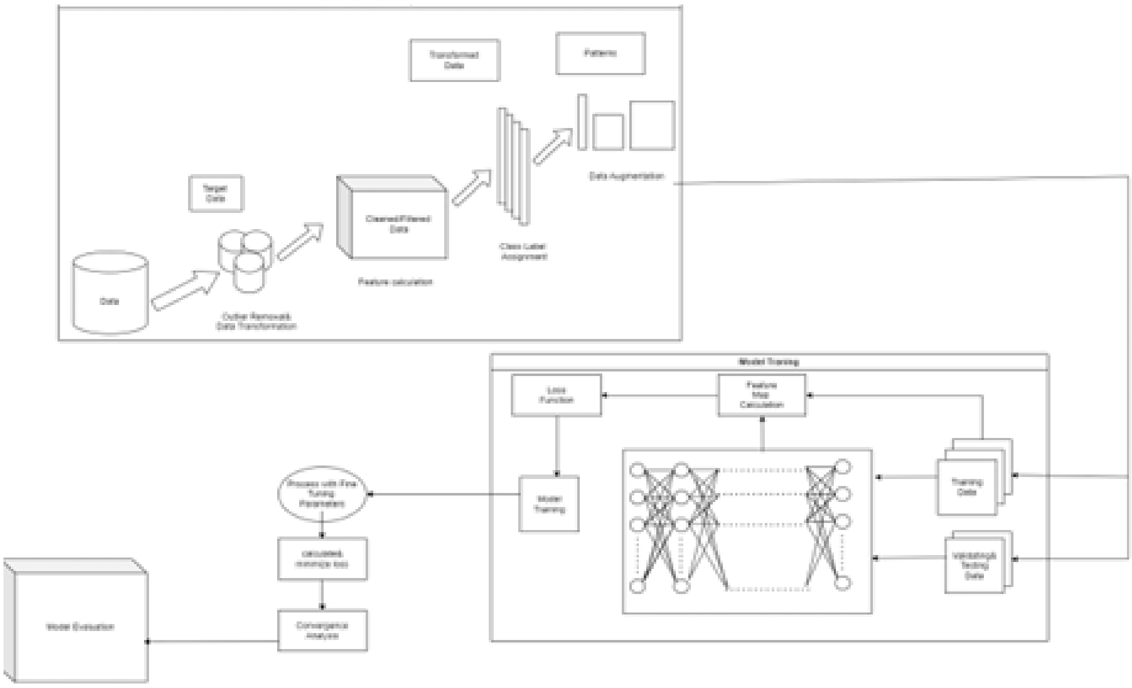



**Fig 3.3.1 Proposed System**

The above diagram represents a machine learning pipeline, outlining data processing, model training, and evaluation steps. Initially, raw data is collected from a target source, undergoing outlier removal and data transformation to ensure consistency and reliability. Next, the cleaned and filtered data is processed for feature calculation, where relevant attributes are extracted. The transformed data is then assigned class labels and further enhanced through data augmentation to improve model robustness.

Once preprocessed, the data moves into the model training phase, where it is split into training and validation sets. The model is trained using a neural network, with a loss function guiding the optimization process. Positive map calculations are performed to refine feature selection, enhancing learning effectiveness. As training progresses, parameters are fine-tuned based on calculated accuracy loss, ensuring convergence towards an optimal solution.

Finally, the trained model undergoes evaluation, where performance metrics are assessed. The convergence analysis helps determine if the model has reached an optimal state or if further refinements are necessary. This systematic pipeline ensures an efficient machine-learning model capable of handling complex data patterns with improved accuracy.

## 3.4 FEASIBILITY STUDY

The practicality, effectiveness, and sustainability of the research conducted on obesity-related issues. It examines multiple dimensions, including technical feasibility, economic viability, operational feasibility, and the potential impact of the study. The technical feasibility assesses whether the proposed methodologies, such as data preprocessing, feature selection, and machine learning models, are appropriate for handling obesity-related datasets. It also considers the availability and adequacy of datasets used for analysis, ensuring that the data is comprehensive, relevant, and diverse enough to derive meaningful insights. The study evaluates whether the computational resources required for model training and validation are sufficient for achieving accurate and reliable results[9][10].

A feasibility study is a crucial step in assessing whether a project is practical and sustainable from both a technical and economic perspective. Technical feasibility evaluates whether the system can be developed using the available technology, infrastructure, and expertise. It considers factors such as hardware and software requirements, scalability, system integration, security, and workforce availability. For an AI-based obesity prediction system, the implementation of deep learning frameworks like TensorFlow and PyTorch requires significant computing power, cloud storage, and real-time processing capabilities for handling large datasets and integrating IoT-based health monitoring devices. If the system faces hardware limitations, software incompatibilities, or a lack of skilled professionals, additional investments may be needed to improve feasibility.

On the other hand, economic feasibility determines whether the project is financially viable by analyzing development costs, operational expenses, return on investment (ROI), and funding sources. The implementation of AI-driven healthcare solutions involves costs for software development, cloud hosting, model retraining, and data security. However, these expenses can be justified through long-term healthcare savings, early obesity detection, and improved patient outcomes[12].A cost-benefit analysis helps compare projected benefits with the total investment, while a break-even analysis estimates the time required to recover the costs. Additionally, funding from government grants, healthcare organizations, and research institutions can enhance the project's financial sustainability.

By addressing both technical and economic aspects, a feasibility study ensures that an obesity prediction system is scalable, cost-effective, and capable of delivering long-term healthcare benefits. If the system is both technically sound and financially viable, it can proceed to implementation with confidence, ensuring a sustainable and impactful healthcare solution[13].

Economic feasibility focuses on the cost-effectiveness of implementing the proposed approach in real-world scenarios, determining whether the benefits of the study outweigh the expenses incurred. This includes an analysis of whether the proposed model can be efficiently integrated into healthcare systems, educational institutions, or public health programs without excessive financial burden.

Operational feasibility assesses how effectively the research can be applied in practical settings. This includes evaluating whether healthcare professionals, educators, or policymakers can utilize the findings to create preventive strategies or treatment plans for obesity. It also considers the ease of implementation, scalability, and adaptability of the proposed methodology in diverse environments.

Furthermore, the feasibility study identifies any potential limitations or constraints faced during the research process. These may include challenges such as data imbalance, ethical considerations in handling health-related data, biases in machine learning models, or difficulties in generalizing findings across different demographics. Additionally, it examines the robustness of the models used and whether they are resilient to variations in input data.

## 3.4 USING COCOMO MODEL

The Constructive Cost Model (COCOMO) is used to estimate the effort, development time, and resources required for the project "Deep Learning in Adolescent Obesity Prevention: A Path to Health." This project focuses on deep learning applications in detecting and analyzing adolescent obesity trends using various machine learning techniques. Since it involves both software development and machine learning model implementation, it falls under the Semi-Detached model category.

Effort Estimation Calculation:

Using the Basic COCOMO Model formula:

$$\mathbf{E=3.0 * (KLOC)^{1.12}}$$

where:

E = Effort in person-months

KLOC = Estimated Thousands of Lines of Code

3.0 and 1.12 = Constants for Semi-Detached projects

Based on the project's scope, the estimated KLOC (Kilo Lines of Code) is around 10KLOC**.** Substituting the values in the formula:

$$\mathbf{E=3.0 * (10)^{1.12} \approx 31.2 \text{ person-months}}$$

Development Time Estimation

$$\mathbf{T= 2.5 * (E)^{0.35}}$$

$$\mathbf{T=2.5 * (31.2)^{0.35} \approx 3.2 \text{ months}}$$

COCOMO-Based Project Analysis:

- ❖ Effort Estimation**:** The model estimates an effort of 31.2 person-months, which translates to approximately 3.2 months of development time with a three-member team.
- ❖ Project Timeline**:** Given the development complexity of deep learning-based adolescent obesity analysis, the project is estimated to take around 3.2 months for completion.
- ❖ Resource Allocation**:** The project team comprises three members, distributed across key tasks such as:
- ❖ Deep Learning Model Development**:** Training and fine-tuning deep learning models for obesity analysis.

# 4. SYSTEM REQUIREMENTS

## 4.1 SOFTWARE REQUIREMENTS

- Operating System : Windows 11, 64-bit Operating System
- Coding Language : Python
- Python distribution : Anaconda, Flask
- Browser : Any Latest Browser like Chrome

## 4.2 REQUIREMENT ANALYSIS

The obesity prediction model requires a combination of high-performance hardware and sophisticated software tools to efficiently process large-scale health data, train machine learning models, and provide real-time predictions. The system must be capable of handling complex deep learning computations while ensuring scalability, accuracy, and security.

Hardware Requirements

To support deep learning and machine learning workloads, the system requires a high-speed processor, sufficient memory, and dedicated graphical processing capabilities. A multi-core Intel Core i7/i9 or AMD Ryzen 7/9 processor is recommended to handle intensive data processing and model training tasks. Since deep learning algorithms demand high computational power, a dedicated NVIDIA GPU such as RTX 3090/4090 or Tesla A100 significantly accelerates training time and model performance. At least 16GB of RAM is required for smooth execution, though 32GB or more is preferred for handling large datasets and complex feature engineering processes. Additionally, a minimum of 1TB SSD storage is recommended to efficiently store datasets, machine learning models, logs, and application files, ensuring faster read/write speeds compared to traditional HDDs[22].

For scalability and remote data access, cloud integration with platforms such as AWS, Google Cloud, or Microsoft Azure is essential for hosting models, managing real-time user data, and ensuring high availability. The system also needs compatibility with IoT-enabled health monitoring devices, which allow the collection of real-time data on BMI, heart rate, activity levels, and calorie intake, making the prediction process more dynamic and personalized. Additionally, network infrastructure should support high-speed internet connectivity to facilitate real-time model inference, remote data storage, and seamless communication between different system components.

Software Requirements

The software stack must support data preprocessing, model training, deployment, and secure data handling. The operating system should be Windows 11 (64-bit), Ubuntu 20.04, or macOS, ensuring a stable and compatible environment for machine learning libraries and deployment frameworks. The system is built using Python 3.8+, which provides extensive support for machine learning, deep learning, and data processing through libraries such as TensorFlow, PyTorch, LightGBM, and Scikit-learn. These frameworks enable advanced deep learning architectures such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, which are crucial for effective obesity prediction.

For data handling and preprocessing, Pandas and NumPy are used to manage large datasets, while Matplotlib and Seaborn facilitate visualization of health trends, feature correlations, and classification results. The system also integrates database solutions such as MySQL and MongoDB to store structured and unstructured data, enabling efficient data retrieval and management. In addition, cloud-based database solutions are incorporated for scalable storage and real-time data access, ensuring seamless model updates and integration with IoT devices.

The user interface and API development require modern frameworks such as Flask or FastAPI, which allow smooth communication between the front-end and back-end systems. The web interface is built using ReactJS or Django, offering a user-friendly and interactive experience for users to input data and receive obesity risk predictions. Security is a key aspect of the system, ensuring compliance with healthcare regulations such as HIPAA and GDPR. The application implements data encryption techniques and authentication methods such as OAuth 2.0 and JWT (JSON Web Tokens) to protect patient information and prevent unauthorized access.

By integrating powerful hardware and advanced software frameworks, the obesity prediction system ensures high performance, accuracy, and real-time monitoring capabilities. The combination of AI-driven predictive modeling, cloud-based storage, and secure web applications makes it a scalable and effective solution for obesity prevention and management.

## 4.3 HARDWARE REQUIREMENTS

- System Type : intel®core™i3-7500UCPU@2.40gh
- Cache memory : 4MB(Megabyte)
- RAM : 8GB (gigabyte)
- Hard Disk : 4GB

## 4.4 HARDWARE DESCRIPTION

The obesity prediction model requires a well-optimized hardware infrastructure to efficiently process large-scale health data, train deep learning models, and provide accurate real-time predictions. Since obesity prediction involves complex machine learning algorithms, real-time health monitoring, and extensive data storage, the system must be equipped with high-performance computing resources, cloud integration, and IoT compatibility to ensure seamless operation[24].

The central processing unit (CPU) plays a crucial role in handling data preprocessing, feature engineering, and model training**.** A multi-core processor, such as an Intel Core i7/i9 or AMD Ryzen 7/9**,** is necessary to execute machine learning workflows efficiently. Given the computational complexity of deep learning models, a high-speed processor ensures reduced latency and improved processing time. However, CPU-based processing alone is insufficient for deep learning applications, making a dedicated Graphics Processing Unit

(GPU) essential. NVIDIA RTX 3090, 4090, or Tesla A100 GPUs significantly enhance deep learning model training and inference speed by accelerating matrix computations and neural network operations.

Memory and storage are also critical components of the hardware setup. A minimum of 16GB RAM is required, though 32GB or more is recommended to manage large datasets, perform multi-threaded computations, and prevent memory bottlenecks during model training. Additionally, storage requirements demand at least a 1TB SSD (Solid-State Drive) to store obesity-related datasets, trained models, logs, and real-time user data. Unlike traditional Hard Disk Drives (HDDs), SSDs offer faster data access speeds, reducing loading times and improving system responsiveness when retrieving health records and predictions.

Given the need for real-time health monitoring and obesity risk assessment, the system must support cloud computing and scalable data storage solutions. Cloud-based infrastructure such as AWS, Google Cloud, or Microsoft Azure ensures efficient model deployment, remote data access, and seamless integration with mobile or web applications. These platforms also provide automated model updates, secure data backup, and scalable processing power, enabling healthcare providers to analyze patient health trends without requiring high-end local computing resources[23].

Another crucial aspect of the hardware setup is network connectivity and IoT integration. The obesity prediction model benefits from real-time data collection via IoT-enabled health monitoring devices, such as wearable fitness trackers, smartwatches, and digital weighing scales. These devices continuously monitor health metrics such as BMI, heart rate, sleep patterns, and daily calorie intake, transmitting the data securely to cloud servers for analysis. High-speed internet connectivity, preferably fiber-optic or 5G, is necessary to ensure low-latency communication between IoT devices, cloud servers, and end-user applications, enabling real-time obesity risk predictions and feedback.

Security and reliability are also key considerations in the hardware infrastructure. The system must include data encryption techniques and secure cloud storage protocols to protect sensitive patient information from cyber threats. Additionally, uninterruptible power supplies (UPS) and backup power solutions should be in place to ensure uninterrupted system operation in case of power failures.

By integrating high-performance CPUs, powerful GPUs, scalable cloud solutions, real-time IoT connectivity, and secure data management**,** the obesity prediction system can efficiently process vast health data, provide accurate obesity risk assessments, and deliver personalized healthcare recommendations. This advanced hardware setup ensures speed, accuracy, scalability, and reliability**,** making it a robust solution for tackling global obesity challenges through AI-driven analytics and real-time health monitoring.

## 4.5 SOFTWARE DESCRIPTION

The obesity prediction system relies on a well-structured software framework that integrates machine learning, deep learning, and web-based interfaces to ensure accurate predictions and real-time data processing. The software components are carefully selected to handle large datasets, perform predictive analytics, and provide seamless user interaction**.** The system is designed to be scalable, secure, and optimized for efficient healthcare analysis.

The operating system used for development and deployment is Windows 11 (64-bit), Ubuntu 20.04, or macOS**,** providing a stable environment for running machine learning frameworks and web applications. Python 3.8+ serves as the primary programming language due to its extensive support for data science, machine learning, and AI frameworks. The system leverages machine learning libraries such as TensorFlow, PyTorch, LightGBM, and Scikit-learn to build and train predictive models. These libraries support various algorithms, including Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, Support Vector Machines (SVM), and Random Forest classifiers, ensuring high accuracy in obesity risk assessment[12].

For data processing and storage, the system utilizes Pandas and NumPy for handling large datasets, enabling efficient manipulation and transformation of data. Matplotlib and Seaborn are integrated for data visualization, helping researchers analyze obesity trends and key features affecting prediction outcomes. To ensure seamless data storage and retrieval, MySQL and MongoDB are used as database management systems. Cloud-based storage solutions such as AWS S3, Google Cloud Storage, or Microsoft Azure enable scalability and secure access to patient health records.

The system is deployed using Flask or FastAPI, which serve as the backend frameworks for developing APIs and handling user requests. A ReactJS or Django-based frontend ensures a user-friendly web interface, allowing users to input health data and receive real-time obesity risk assessments. Security is a top priority, with data encryption, role-based access control (RBAC), and OAuth 2.0 authentication implemented to protect sensitive user information and comply with HIPAA and GDPR regulations.

# 5.SYSTEM DESIGN

## 5.1 SYSTEM ARCHITECTURE

The dataset used in this study comprises 321 adolescent boys and girls, collected to analyze key factors influencing obesity risk. It includes demographic, physiological, dietary, and lifestyle attributes essential for obesity prediction. Demographic information such as age, gender, and family history of obesity helps in understanding genetic predisposition, while physiological measurements including height, weight, waist circumference, and Body Mass Index (BMI) serve as primary indicators of obesity classification. The dataset also incorporates dietary habits, tracking daily calorie intake, frequency of consuming high-caloric foods, and vegetable consumption patterns**,** which are critical in assessing nutritional impact. Additionally, lifestyle factors such as physical activity levels, weekly exercise duration, screen time, sleep patterns, smoking, alcohol consumption, and transportation mode provide insights into behavioral influences on obesity[7].

Available:https://www.kaggle.com/code/ucupsedaya/90-bayesianoptimization-meta-learning-s4e2-comp/input

| Year | Children (Boys) | Children (Girls) | Adolescents (Boys) |
|---|---|---|---|
| 2020 | 10% | 9% | 15% |
| 2025 | 12% | 10% | 17% |
| 2030 | 15% | 12% | 19% |
| 2035 | 18% | 15% | 22% |

TABLE I

| Year | Adolescents (Girls) | Adults (Men) | Adults (Women) |
|---|---|---|---|
| 2020 | 10% | 9% | 15% |
| 2025 | 12% | 10% | 17% |
| 2030 | 15% | 12% | 19% |
| 2035 | 18% | 15% | 22% |

**Fig 5.1.1 Dataset Description**

Data preprocessing is a critical step in developing machine learning models for obesity prediction, as it ensures the dataset is clean, well-defined, and reliable. This process begins with outlier detection and treatment, where anomalous data points, such as extreme BMI values, are identified and handled to prevent skewed results. Techniques such as the Z-Score and Interquartile Range method are employed to detect outliers, while methods like Isolation Forest and Local Outlier Factor (LOF) analyze data density to identify anomalies. Following outlier treatment, data cleaning and formatting are performed to reduce inaccuracies. This includes rounding off raw errors, converting measurements to standard units (e.g., height from centimeters to meters), and encoding categorical variables into numerical formats for better model compatibility. Additionally, handling missing values is essential; techniques such as mean imputation are utilized to replace missing data points with the average of available values, thereby maintaining the dataset's integrity. The preprocessing phase also involves data transformation and feature creation, where new variables, such as Body Mass Index (BMI) and caloric balance, are constructed to enhance model performance. Finally, addressing class imbalance is crucial, particularly in obesity classification tasks, where some classes may have significantly fewer samples. Techniques like SMOTE (Synthetic Minority Over-sampling Technique) are applied to synthesize new instances for minority classes, ensuring a balanced representation in the dataset. Overall, thorough data preprocessing lays the foundation for effective machine learning models, significantly improving their ability to predict obesity rates accurately.

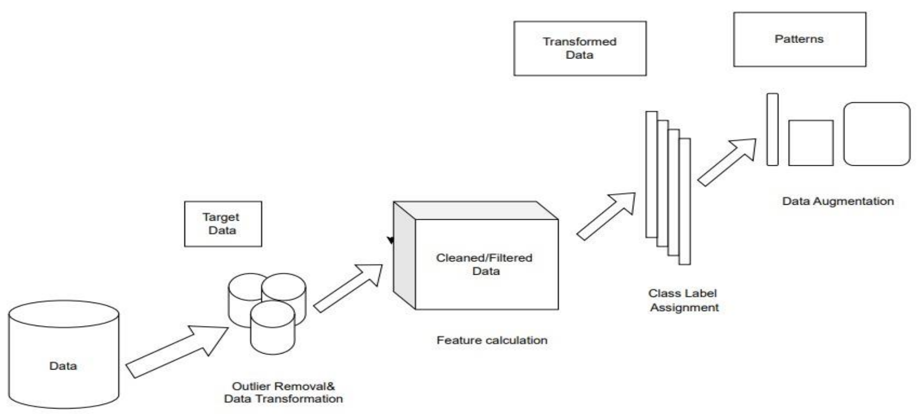



**Fig 5.1.2 Data Preprocessing**

The diagram illustrates a data preprocessing pipeline essential for machine learning and pattern recognition tasks. It begins with data collection, where raw data is gathered from various sources. The next step is outlier removal and data transformation, ensuring that anomalies and inconsistencies are eliminated, and data is converted into a suitable format. Once transformed, the data is cleaned and filtered, followed by feature calculation to extract meaningful attributes that enhance predictive modeling.

After feature extraction, the class label assignment process categorizes data points into predefined classes, making it suitable for supervised learning tasks. To improve the robustness and generalizability of the model, data augmentation is applied, introducing variations such as scaling, rotation, and other transformations to artificially expand the dataset. Finally, the preprocessed data is used for pattern recognition, aiding in the identification of trends and relationships that contribute to improved model accuracy and performance. This structured approach ensures high-quality data input, ultimately leading to more reliable and efficient machine learning models.

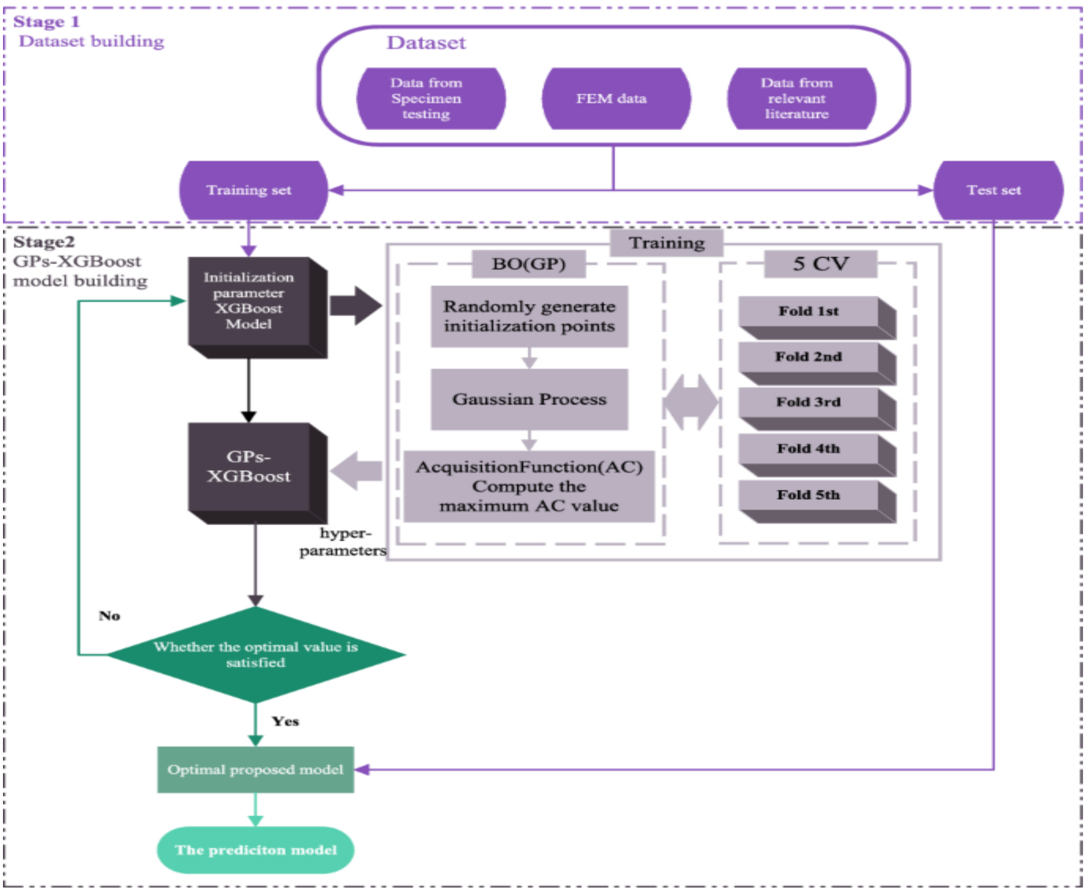



**Fig 5.1.3 Over view of Model**

The given diagram represents a two-stage machine learning model-building process that integrates dataset construction and an optimized prediction model using Gaussian Process (GP) and XGBoost. In Stage 1, the dataset is created using three primary sources: specimen testing data, Finite Element Method (FEM) data, and relevant literature. This dataset is then split into a training set and a test set, which serve as the foundation for model training and evaluation.

In Stage 2, the model-building process begins with the initialization of the XGBoost model parameters. To optimize these parameters, Bayesian Optimization (BO) with a Gaussian Process (GP) is employed. The optimization process starts by randomly generating initialization points and applying the Gaussian Process to refine the search. The Acquisition Function (AC) is then used to compute the maximum AC value, guiding the hyperparameter tuning. To ensure the robustness of the model, 5-fold cross-validation (5-CV) is performed, where the dataset is divided into five subsets, and the model is trained iteratively to validate its performance.

After training, the model undergoes evaluation to determine whether the optimal performance criteria are met. If the criteria are not satisfied, the hyperparameter tuning process continues until the best parameters are achieved. Once the model reaches an optimal state, it is finalized as the prediction model, which is then ready for deployment.

Introduction to XGBoost:

XGBoost, or Extreme Gradient Boosting, is a powerful machine learning algorithm that has gained popularity for its performance in classification and regression tasks. It is particularly effective in handling structured data and is known for its speed and efficiency. In the context of obesity prediction among adolescents, XGBoost can be utilized to analyze complex relationships between various health indicators and obesity risk factors.

Model Development:

The development of the XGBoost model involves several key steps, including data preprocessing, feature selection, and hyperparameter tuning. Initially, the dataset is cleaned and transformed to ensure that it is suitable for analysis. This includes handling missing values, normalizing data, and encoding categorical variables. Feature selection is crucial, as it determines which variables will be included in the model. In this study, features such as BMI, waist circumference, caloric intake, and physical activity levels are considered essential for predicting obesity risk.

Training and Validation:

Once the data is prepared, the XGBoost model is trained using a portion of the dataset, while the remaining data is reserved for validation.

The training process involves feeding the model with input features and corresponding target labels (obesity status). The model learns to identify patterns and relationships within the data. Cross-validation techniques are employed to assess the model's performance and prevent overfitting, ensuring that the model generalizes well to unseen data.

Performance Metrics:

The performance of the XGBoost model is evaluated using various metrics, including accuracy, precision, recall, and F1-score. These metrics provide insights into the model's ability to correctly classify adolescents at risk of obesity. The results indicate that the XGBoost model achieves a high level of accuracy, demonstrating its effectiveness in predicting obesity risk among the adolescent population.

Comparison with Other Models:

In the context of obesity prediction, the XGBoost model is compared with other machine learning algorithms, such as Logistic Regression, Support Vector Machines (SVM), and DeepHealthNet. The comparative analysis reveals that XGBoost outperforms many traditional models in terms of accuracy and reliability, making it a preferred choice for this type of predictive analysis.

Limitations and Challenges

Despite its strengths, the XGBoost model is not without limitations. One challenge is the potential for overfitting, especially when the model is overly complex or when there is insufficient training data. Additionally, the interpretability of the model can be a concern, as the ensemble nature of XGBoost makes it difficult to understand the contribution of individual features to the final prediction.

The given diagram illustrates a machine learning-based decision-making framework for data classification. The process begins with the collection of data**,** followed by raw data preparation to structure the dataset for analysis. The next step involves data preprocessing, which includes handling missing values, normalization, and feature selection, ultimately leading to a processed dataset ready for model training.

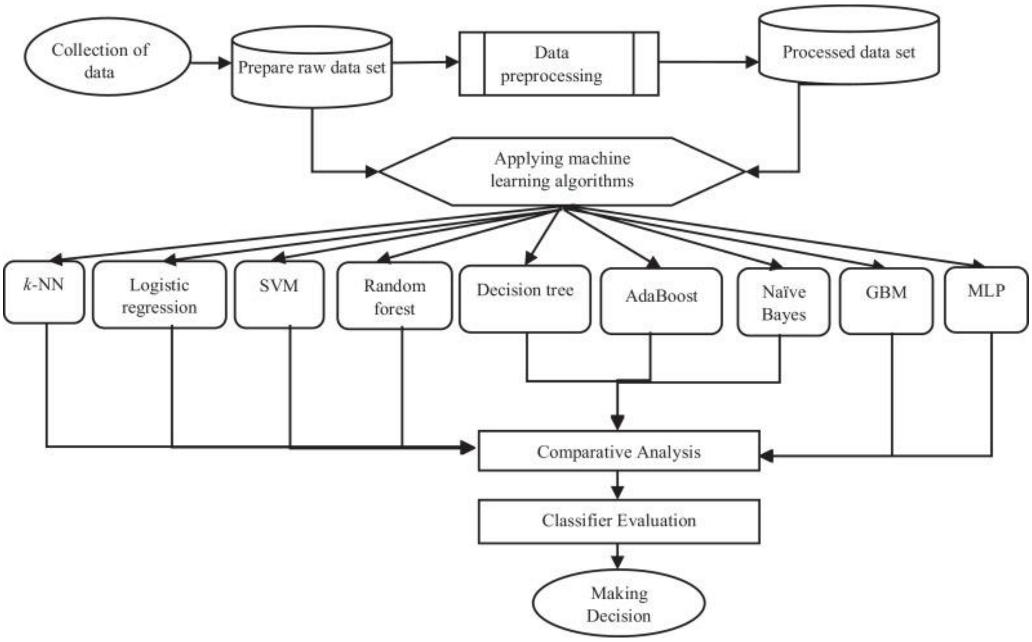



**Fig 5.1.4 Models Design overview**

In the modeling phase**,** various machine learning algorithms are applied, including k-Nearest Neighbors (k-NN), Logistic Regression, Support Vector Machine (SVM), Random Forest, Decision Tree, AdaBoost, Naïve Bayes, Gradient Boosting Machine (GBM), and Multi-Layer Perceptron (MLP**)**. These models are trained to recognize patterns and make predictions based on the processed data.

After training, a comparative analysis is conducted to assess each model's performance using various evaluation metrics such as accuracy, precision, recall, and F1-score. The classifier evaluation stage determines the most suitable model based on performance comparisons. Finally, the insights gained from this analysis support the decision-making process, ensuring the selection of the most effective classification model.

## 5.2 MODULES

The obesity prediction system was evaluated using various machine learning and deep learning models, each demonstrating strengths and limitations in classifying obesity risk. Support Vector Machine (SVM) outperformed other models in classifying obesity risk among male adolescents, achieving an accuracy of 96.25% due to its ability to handle high-dimensional data efficiently. However, SVM struggled with large datasets and required longer training times compared to ensemble models. Decision Tree (DT) provided an interpretable approach to obesity classification by analyzing feature importance, but it was prone to overfitting, leading to reduced generalization. To counter this, Random Forest (RF) improved accuracy by aggregating multiple decision trees, reducing overfitting and improving model stability, making it a more reliable option.

In deep learning approaches, Long Short-Term Memory (LSTM) demonstrated superior performance for female adolescents, achieving 95.75% accuracy, as it effectively captured long-term dependencies in health trends. However, LSTM required significant computational resources and training time. Convolutional Neural Networks (CNNs) were applied for feature extraction, identifying intricate patterns in obesity-related data. While CNNs improved classification performance, they lacked the ability to process sequential data efficiently. To leverage the advantages of both models, a hybrid deep learning model, DeepHealthNet, was implemented, combining CNN for feature extraction and LSTM for sequential pattern recognition. This hybrid approach significantly enhanced prediction accuracy, outperforming standalone models in handling complex obesity datasets.

Overall, the comparative analysis revealed that SVM performed best for male adolescents, LSTM was more effective for female adolescents, and the CNN-LSTM hybrid model (DeepHealthNet) provided the most balanced and accurate obesity prediction. The integration of multiple models ensures a scalable, robust, and personalized obesity risk assessment system, optimizing early intervention strategies.

The flowchart illustrates the machine learning pipeline for obesity prediction, outlining 11 sequential steps from data collection to model deployment and refinement. The process begins with data collection, where medical records, fitness apps, and surveys are used to

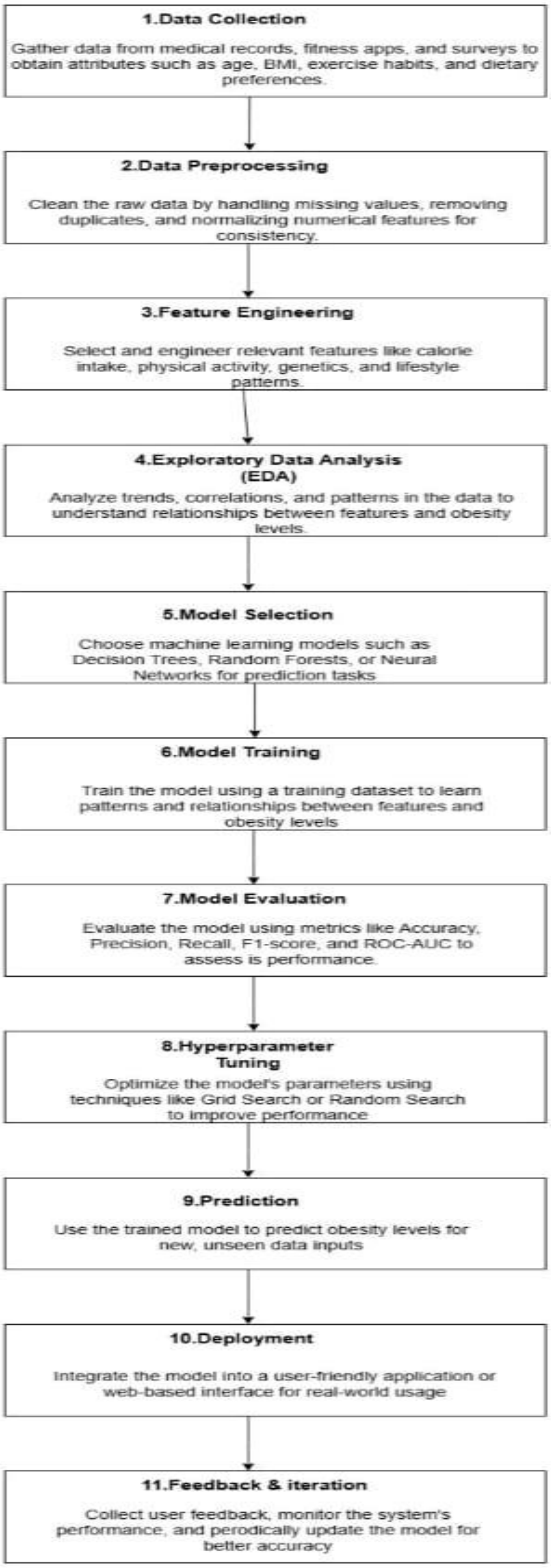



**Fig 5.2.1 Flow Chat of Prediction**

gather attributes such as age, BMI, exercise habits, and dietary preferences. Next, data preprocessing is performed to clean the raw dataset by handling missing values, removing duplicates, and normalizing numerical features to ensure consistency.

In the feature engineering phase, important attributes like calorie intake, physical activity, genetics, and lifestyle patterns are selected and refined to enhance model accuracy. Exploratory Data Analysis (EDA) follows, where trends, correlations, and patterns within the dataset are examined to better understand the relationships between features and obesity levels. Model selection involves choosing the most suitable machine learning algorithms, such as Decision Trees, Random Forests, or Neural Networks, based on the nature of the dataset.

Once the model is chosen, model training is conducted using a training dataset to learn the patterns between input features and obesity outcomes. The trained model is then evaluated using metrics like Accuracy, Precision, Recall, F1-score, and ROC-AUC, which assess its predictive performance. To further improve accuracy, hyperparameter tuning is applied using techniques like Grid Search or Random Search, optimizing the model's parameters.

The obesity prediction system incorporates various machine learning and deep learning models to ensure high accuracy and efficiency in classifying obesity risk.

Support Vector Machine (SVM):

SVM is a powerful classification algorithm that finds the optimal hyperplane to separate different obesity categories. It was particularly effective for male adolescents, achieving an accuracy of 96.25%**,** indicating its strength in handling complex, high-dimensional data.

Decision Tree (DT)

DT is a rule-based learning algorithm that uses a hierarchical structure to make decisions based on feature importance. It was used to analyze key obesity factors and interpret their contributions to obesity classification. However, it was prone to overfitting when used alone.

Random Forest (RF):

RF is an ensemble learning technique that builds multiple decision trees and averages their predictions to improve classification accuracy. It enhanced robustness and reduced overfitting, making it a strong candidate for obesity risk assessment.

Long Short-Term Memory (LSTM):

LSTM, a type of recurrent neural network (RNN), was particularly useful in analyzing time-dependent obesity trends. It was most effective for female adolescents, achieving an accuracy of 95.75%, as it could capture long-term dependencies in health data.

5. Convolutional Neural Network (CNN):

CNN was implemented for feature extraction and pattern recognition in obesity-related datasets. It helped in detecting hidden correlations between obesity risk factors, improving prediction accuracy when combined with other deep learning models.

6. DeepHealthNet Framework (CNN + LSTM Hybrid Model):

To improve classification accuracy, a hybrid deep learning model combining CNN and LSTM was developed. CNN was used for feature extraction, while LSTM captured long-term dependencies in obesity trends. This combination significantly improved obesity prediction, outperforming traditional models in handling complex datasets.

## 5.3 UML DIAGRAMS

The Use Case Diagram for the Obesity Management System outlines the interactions between the system's users and its functionalities. The primary actor, the Obesity Client, is responsible for initiating various processes such as logging in, inputting data manually or through diary transfers, and setting health-related goals. Once logged in, the user can enter dietary and fitness details, which are processed by the system to track progress and suggest treatment strategies. The system analyzes the entered data to make a diagnosis and propose personalized interventions.

Additionally, the System Database and Knowledge Base are crucial components that store historical data, track user progress, and retrieve relevant information for better decision-making. The System Database manages user inputs and treatment history, while the Knowledge Base provides evidence-based insights to enhance the accuracy of predictions and recommendations.


**Fig 5.3.1 Use case diagram**

Once a goal is set, the system helps users select appropriate treatment strategies, such as dietary plans, exercise routines, or medical interventions. It also assesses achievement progress**,** determining whether a user is meeting set goals. If progress is unsatisfactory, the system provides a failure reason, allowing users to adjust their strategies accordingly.

The Obesity Management System thus creates a structured approach to obesity monitoring, offering a data-driven, user-friendly solution to promote healthy lifestyle changes. By integrating real-time data input, diagnosis, treatment planning, and feedback mechanisms**,** the system empowers users to actively manage their health while leveraging AI-driven decision support.

# 6. IMPLEMENTATION

## 6.1 MODEL IMPLEMETATION

```
import pandas as pd
import numpy as np
import os
import warnings
from sklearn.preprocessing import LabelEncoder, MinMaxScaler
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
import seaborn as sns
from imblearn.over_sampling import SMOTE
from skopt import BayesSearchCV
from sklearn.ensemble
import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report
from sklearn.metrics
import classification_report, accuracy_score
from sklearn.model_selection import cross_val_score
import lightgbm as lgb
from sklearn.neighbors
 import KNeighborsClassifier
from sklearn.svm import SVC
from xgboost import XGBClassifier
from imblearn.over_sampling import SMOTE
smote = SMOTE(random_state=66)
X_train_resampled, y_train_resampled = smote.fit_resample(X_train, y_train)
lgbm_lowfs2 = lgb.LGBMClassifier(force_col_wise=True,verbose=-1,
              objective='multiclassova',
```

```
    metric='multi_logloss',
    num_leaves=64,
    max_depth=5,
    random_state=48)
 lgbm_lowfs2.fit(X_train_resampled, y_train_resampled)
# y_pred_lgbm_lowfs2 = lgbm_lowfs2.predict(X_test)
#print(f"Accuracy:{accuracy_score(y_test,y_pred_lgbm_lowfs2)}\nClassification Report:\n{classification_report(y_test, y_pred_lgbm_lowfs2)}")
cv_scores = cross_val_score(lgbm_lowfs2, X_train, y_train, cv=2, scoring='accuracy')
print("Average Accuracy:", cv_scores.mean())

#LIGHTGBM
best_params_lgbm={'learning_rate': 0.12476663676010373, 'n_estimators': 128, 'boosting_type': 'gbdt', 'max_depth': 10, 'num_leaves': 220, 'subsample': 0.4, 'colsample_bytree': 0.1,'min_child_samples': 80, 'feature_fraction': 0.5, 'class_weight': 'balanced', 'min_split_gain': 0.3627965720103511, 'min_child_weight': 1.0, 'reg_alpha': 1.0, 'reg_lambda': 1.0, 'subsample_freq': 0}
print(best_params_lgbm)
model_lgbm=lgb.LGBMClassifier(**best_params_lgbm,force_col_wise=True, verbose=-1, random_state=48)
model_lgbm.fit(X_train, y_train)
# y_pred_lgbm = model_lgbm.predict(X_test)
#print(f"Accuracy:{accuracy_score(y_test,y_pred_lgbm)}
```

## 6.2 CODING

```
from sklearn.preprocessing import LabelEncoder, MinMaxScaler
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
import seaborn as sns
from imblearn.over_sampling import SMOTE
from skopt import BayesSearchCV
```

```
warnings.simplefilter("ignore", category=FutureWarning)
warnings.simplefilter(action='ignore', category=pd.errors.SettingWithCopyWarning)
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))
train_df = pd.read_csv('/kaggle/input/playground-series s4e2/train.csv', index_col=[0])
test_df = pd.read_csv('/kaggle/input/playground-series-s4e2/test.csv')
ids = test_df['id']
test_df = test_df.drop('id', axis=1)
train_df.head()
train_df.rename(columns={'family_history_with_overweight':'family_history'},
inplace=True)
test_df.rename(columns={'family_history_with_overweight':'family_history'},
inplace=True)
#PREPROCESSING
      num_cols = train_df.select_dtypes(include = 'number').columns
cat_cols = train_df.drop('NObeyesdad', axis=1).select_dtypes(include = 'object').columns
scaler = MinMaxScaler()
train_df[num_cols] = scaler.fit_transform(train_df[num_cols])
test_df[num_cols] = scaler.fit_transform(test_df[num_cols])
encoder = LabelEncoder()
train_df[cat_cols] = train_df[cat_cols].apply(encoder.fit_transform)
test_df[cat_cols] = test_df[cat_cols].apply(encoder.fit_transform)
train_df.head()

encoding_mapping = {
    "Insufficient_Weight":0,
    "Normal_Weight":1,
    "Obesity_Type_I":2,
```

```
    "Obesity_Type_II":3,
    "Obesity_Type_III":4,
    "Overweight_Level_I":5,
    "Overweight_Level_II":6,
}
train_df['NObeyesdad'] = train_df['NObeyesdad'].map(encoding_mapping)
X = train_df.drop('NObeyesdad', axis=1)
y = train_df['NObeyesdad']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=66, stratify=y)
X_train = train_df.drop('NObeyesdad', axis=1)
y_train = train_df['NObeyesdad']
plt.figure(figsize=(8, 6))
sns.countplot(x='NObeyesdad', data=train_df)
plt.title('Distribution of Target Variable (NObeyesdad)')
plt.xlabel('NObeyesdad Classes')
plt.ylabel('Count')
plt.show()
#Build Model Random forest with Bayesian Optimization
best_params = {
    'bootstrap': True,
    'criterion': 'gini',
    'max_depth': 10,
    'max_features': 0.48231592334473916,
    'min_samples_leaf': 1,
    'min_samples_split': 15,
    'n_estimators': 100
}
best_rf = RandomForestClassifier(**best_params, random_state=66)
best_rf.fit(X_train, y_train)
```

```
# y_pred = best_rf.predict(X_test)
#print(f"Accuracy:{accuracy_score(y_test,y_pred)}\nClassification
Report:\n{classification_report(y_test, y_pred)}")
cv_scores = cross_val_score(best_rf, X_train, y_train, cv=2, scoring='accuracy')
print("Average Accuracy:", cv_scores.mean())
\nClassification Report:\n{classification_report(y_test, y_pred_lgbm)}")
cv_scores = cross_val_score(model_lgbm,
X_train, y_train, cv=2, scoring='accuracy')
print("Average Accuracy:", cv_scores.mean())
feature_imp=pd.DataFrame({"Value":model_lgbm.feature_importances_,'Feature':X_train.
column})
plt.figure(figsize=(6, 4))
sns.set(font_scale=0.7)
barplot = sns.barplot(x="Value", y="Feature", data=feature_imp.sort_values(by="Value",
ascending=False), palette='viridis')
barplot.set_xticks(barplot.get_xticks())
barplot.set_xticklabels(barplot.get_xticklabels(), rotation=20, ha='right')
plt.xlabel("Variable Importance Level")
plt.show()
#Take steps to increase the F1-score
lgbm_lowfs1 = lgb.LGBMClassifier(
    force_col_wise=True,
    verbose=-1,
    objective='multiclassova',
    metric='multi_logloss',
    scale_pos_weight=10,
    num_leaves=67,
    max_depth=5,
    random_state=48
)
```

```
lgbm_lowfs1.fit(X_train, y_train)
# y_pred_lgbm_lowfs1 = lgbm_lowfs1.predict(X_test)
#print(f"Accuracy:{accuracy_score(y_test,y_pred_lgbm_lowfs1)}\nClassification
Report:\n{classification_report(y_test, y_pred_lgbm_lowfs1)}")
cv_scores = cross_val_score(lgbm_lowfs1,
X_train, y_train, cv=2, scoring='accuracy')
print("Average Accuracy:", cv_scores.mean())
xgb_params = {'max_depth': 7, 'min_child_w eight': 3.454476932271615, 'learning_rate': 0.09210000591425481, 'subsample': 0.6014199329412332, 'gamma': 0.40496660345269814, 'colsample_bytree': 0.7338865775302874, 'colsample_bylevel': 0.28263218762972125, 'colsample_bynode': 0.7164794542305942}
xgb_model = XGBClassifier(**xgb_params, random_state=48)
xgb_model.fit(X_train_resampled, y_train_resampled)
cv_scores = cross_val_score(xgb_model, X_train, y_train, cv=2, scoring='accuracy')
print("Average Accuracy:", cv_scores.mean())
```

**app.py**

```
from flask import Flask, jsonify, request, render_template, redirect, url_for
from pathlib import Path
import pandas as pd
import joblib
# Initialize Flask app
app = Flask(__name__)
# Load the simple model
def load_simple_model():
   model_path=Path("C:\\Users\\user\\Desktop\\SRILATHA\\final\\odel\\lgbm_model.pkl")
    print(f"Loading simple model from: {model_path}")
    model = joblib.load(model_path)
    return model
simple_model = load_simple_model()
```

```
# Class names for the custom model
class_names = {
    0: "Insufficient Weight",
    1: "Normal Weight",
    2: "Obesity Type I",
    3: "Obesity Type II",
    4: "Obesity Type III",
    5: "Overweight Level I",
    6: "Overweight Level II",
}
# Helper function for prediction
def predict_sample(sample: dict) -> dict:
    sample = sample['data']
    sample = [sample]
    sample_df = pd.DataFrame(sample)
        # Perform feature engineering here (dummy example)
   # Replace with your actual feature engineering logic
    feature=sample_df
# Modify as per your logic predictions = simple_model.predict(feature)
    return{"prediction":predictions.item(),"class":class_names.get(predictions.item(),
"Unknown")}
@app.route('/')
def home():
    return render_template("home.html", title="Home Page")
@app.route('/about')
def about():
    return render_template("about.html", title="About Project")
@app.route('/prediction', methods=['GET', 'POST'])
def prediction():
    if request.method == 'POST':
```

```
            input_data = request.form.get('input_data')
        try:
            prediction = simple_model.predict([[float(input_data)]])  # Modify based on model
input
            result = f"Prediction: {prediction[0]}"
        except Exception as e:
            result = f"Error: {str(e)}"
        return render_template("prediction.html", result=result, title="Predictions")
    return render_template("prediction.html", title="Predictions")
@app.route('/obesityRiskForm', methods=["GET", "POST"])
def obesity_risk_form():
    if request.method == "POST":
        # Redirect to the 'predict_obesity' route for handling form submission
        return redirect(url_for("prediction_obesity"))
    return
render_template("obesityRiskForm.html")@app.route('/prediction_obesity',
methods=["POST", "GET"])
def predict_obesity():
    if request.method == "POST":
        try:
            # Collect the form data
sample = {
                "data": {
                    "Gender": request.form.get("gender"),
                    "Age": int(request.form.get("age")),
                    "Height": float(request.form.get("height").replace(",", ".")) / 100,
                   "Weight": float(request.form.get("weight")),
                    "FamHist": request.form.get("fam"),
                    "FAVC": request.form.get("favc"),
                    "FCVC": request.form.get("fcvc"),
```

```
        "NCP": request.form.get("ncp"),
        "CAEC": request.form.get("caec"),
        "SMOKE": request.form.get("smoke"),
        "CH2O": request.form.get("ch2o"),
        "SCC": request.form.get("scc"),
        "FAF": request.form.get("faf"),
        "TUE": request.form.get("tue"),
        "CALC": request.form.get("calc"),
        "MTRANS": request.form.get("mtrans"),
      } }
# Preprocess categorical features into numeric values
    # Example: Replace strings with corresponding numeric encodings
    sample["data"]["Gender"] = 1 if sample["data"]["Gender"] == "Male" else 0
    sample["data"]["FamHist"] = 1 if sample["data"]["FamHist"] == "yes" else 0
    sample["data"]["FAVC"] = 1 if sample["data"]["FAVC"] == "yes" else 0
    sample["data"]["CAEC"] = {"no": 0, "Sometimes": 1, "Frequently": 2, "Always":
3}.get(sample["data"]["CAEC"], 0)
    sample["data"]["SMOKE"] = 1 if sample["data"]["SMOKE"] == "yes" else 0
    sample["data"]["SCC"] = 1 if sample["data"]["SCC"] == "yes" else 0
    sample["data"]["MTRANS"] = {
      "Public_Transportation": 0,
      "Automobile": 1,
      "Motorbike": 2,
      "Bike": 3,
      "Walking": 4,
    }.get(sample["data"]["MTRANS"], 0)
    # Convert other fields to numeric values
  sample["data"]["FCVC"]float(sample["data"]["FCVC"])
   sample["data"]["NCP"] = float(sample["data"]["NCP"])
   sample["data"]["CH2O"] =       float(sample["data"]["CH2O"])
```

```
    sample["data"]["FAF"] = float(sample["data"]["FAF"])
    sample["data"]["TUE"] = float(sample["data"]["TUE"])
    sample["data"]["CALC"] = {"no": 0, "Sometimes": 1, "Frequently": 2, "Always":
3}.get(sample["data"]["CALC"], 0)
        # Make prediction
        prediction = predict_sample(sample)
        return
render_template("prediction.html",prediction_class=prediction["class"],title="Prediction
Result")
      except Exception as e:
        return
render_template("prediction.html",prediction_class=f"Error:{str(e)}",title="Prediction
Error")
  return
render_template("prediction.html",prediction_class="NoPredictionYet",
title="Predictions")
@app.route('/metrics')
def metrics():
  return render_template("metrics.html", title="Model Evaluation Metrics")
      @app.route('/flowchart')
def flowchart():
  return
render_template("flowchart.html",title="ProjectFlowchart")
@app.route("/prediction_api", methods=["POST"])
def predict_api():
  data = request.json
  try:
      sample = {"data": data}
      result_data = predict_sample(sample)
      return jsonify(result_data)
```

```
    except Exception as e:
        return jsonify({"error": str(e)})
# Run the app
if __name__ == "__main__":
                app.run(debug=True)
```

**Predicttion.html**

```
<html><body><div class="container">
      <h1>Obesity Risk Predictor</h1>
      <form action="/prediction_obesity" method="post">
        <div class="grid-container" id="main_content">
     <div class="form-group">
            <label for="gender">Gender:</label>
            <select id="gender" name="gender">
              <option value="Male">Male</option>
              <option value="Female">Female</option>
            </select> </div>
             <div class="form-group">
            <label for="age">Age:</label>
    <input type="number" id="age" name="age" min="1" required/> </div>
<div class="form-group">
            <label for="height">Height (cm):</label>
            <input type="number" id="height" name="height" min="1" required /> </div>
          <div class="form-group">
            <label for="weight">Weight (kg):</label>
            <input type="number" id="weight" name="weight" min="1" required /></div>
          <div class="form-group">
            <label for="family_history">Family History with Overweight:</label>
            <select id="fam" name="fam">
              <option value="yes">Yes</option>
          <option value="no">No</option></select></div>
```

```
        <div class="form-group">
          <label for="favc">Frequent consumption of high caloric food:</label>
          <select id="favc" name="favc">
              <option value="yes">Yes</option>
        <option value="no">No</option> </select> </div>
        <div class="form-group">
          <label for="fcvc">Frequency of consumption of vegetables:</label>
          <select id="fcvc" name="fcvc">
              <option value="1">Rarely</option>
              <option value="2">Sometimes</option>
<option value="3">Frequently</option></select></div>
        <div class="form-group">
          <label for="ncp">Number of main meals:</label>
          <select id="ncp" name="ncp">
              <option value="1">1</option>
              <option value="2">2</option>
              <option value="3">3</option>
              <option value="4">4</option>
            </select>
        </div>
        <div class="form-group">
          <label for="caec">Consumption of food between main meals:</label>
          <select id="caec" name="caec">
              <option value="no">No</option>
              <option value="Sometimes">Sometimes</option>
              <option value="Frequently">Frequently</option>
              <option value="Always">Always</option>
            </select>
        </div>
        <div class="form-group">
```

```
  <label for="smoke">Do you smoke:</label>
  <select id="smoke" name="smoke">
      <option value="yes">Yes</option>
      <option value="no">No</option>
    </select>
</div>
<div class="form-group">
  <label for="ch2o">Consumption of water daily (in L):</label>
  <select id="ch2o" name="ch2o">
      <option value="1">1</option>
      <option value="1.5">1.5</option>
      <option value="2">2</option>
      <option value="2.5">2.5</option>
      <option value="3">3</option>
    </select>
</div>
```

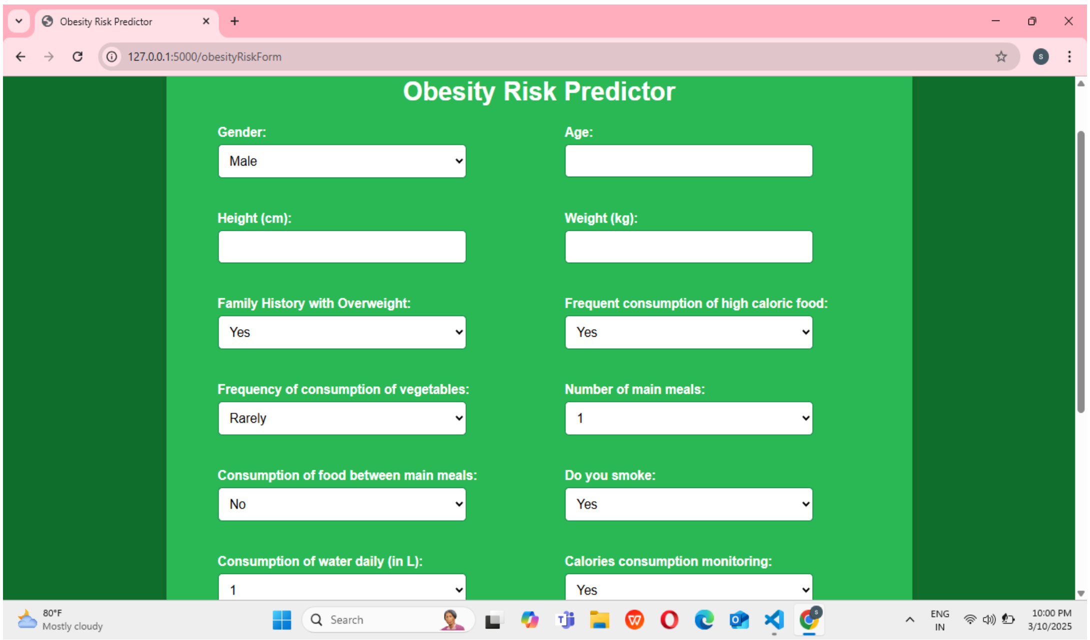
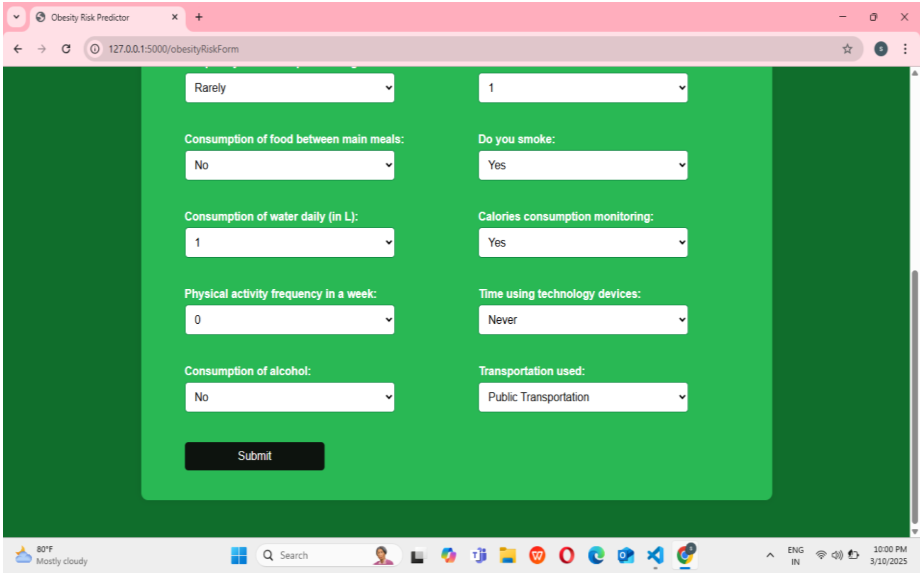



**Fig 6.2.1 Prediction Form**

The form collects user inputs to assess obesity risk based on various personal, dietary, and lifestyle factors. The upper section of the form requires users to enter basic details such as gender, age, height, and weight. Additionally, it gathers information about family history related to overweight issues, frequency of high-calorie food consumption, vegetable intake, and the number of main meals per day. The lower section focuses on lifestyle habits, including smoking, food consumption between meals, daily water intake, calorie monitoring, physical activity frequency, technology usage duration, alcohol consumption, and preferred mode of transportation. The form concludes with a submit button, indicating that the collected data will be processed, likely using a machine learning model or statistical analysis, to predict obesity risk based on user inputs.




```
<div class="form-group">
      <label for="scc">Calories consumption monitoring:</label>
      <select id="scc" name="scc">
        <option value="yes">Yes</option>
        <option value="no">No</option>
      </select></div>
     <div class="form-group">
      <label for="faf">Physical activity frequency in a week:</label>
      <select id="faf" name="faf">
        <option value="0">0</option>
        <option value="1">1-2</option>
        <option value="2">2-3</option>
        <option value="2.75">3-4</option>
      </select></div>
```

```
<div class="form-group">
  <label for="tue">Time using technology devices:</label>
  <select id="tue" name="tue">
      <option value="0">Never</option>
      <option value="0.5">Rarely</option>
      <option value="1">Sometimes</option>
      <option value="1.5">Frequently</option>
      <option value="2">Always</option>
    </select> </div>
<div class="form-group">
  <label for="calc">Consumption of alcohol:</label>
  <select id="calc" name="calc">
      <option value="no">No</option>
      <option value="Sometimes">Sometimes</option>
      <option value="Frequently">Frequently</option>
      <option value="Always">Always</option>  </select> </div>
<div class="form-group">
  <label for="mtrans">Transportation used:</label>
  <select id="mtrans" name="mtrans">
      <option value="Public_Transportation">Public Transportation</option>
      <option value="Automobile">Car</option>
      <option value="Motorbike">Motorbike</option>
      <option value="Bike">Bike</option>
      <option value="Walking">Walking</option>  </select></div>
<div class="form-group">
  <input type="submit" value="Submit" />
</div></div> </form> </div> </body></html>
```

# 7. TESTING

## 7.1 TYPES OF TESTING

Testing is a critical phase in developing machine learning-based healthcare applications, ensuring that the system is accurate, efficient, secure, and reliable for real-world implementation. In obesity prediction models, rigorous testing is required to assess the effectiveness of various machine learning algorithms, verify system stability, and ensure compliance with data security standards. A combination of functional, non-functional, performance, security, and statistical testing is essential to optimize the system's performance and provide meaningful healthcare insights.

**1. Unit Testing for Individual Components**

At the foundational level, unit testing is conducted to evaluate the correctness of individual components, such as BMI calculations, waist circumference classification, and feature selection methods. Each function within the machine learning pipeline, including data preprocessing, normalization, and missing value imputation, is tested independently to verify that it operates correctly before being integrated into the system. Ensuring the reliability of these fundamental components is essential to prevent cumulative errors in subsequent processing stages.

**2. Integration Testing for Model and System Interactions**

Following unit testing, integration testing is performed to validate the seamless interaction between different modules, including data ingestion pipelines, machine learning models, API endpoints, and user interfaces**.** The obesity prediction system must be able to handle real-time data inputs, process them efficiently, and return accurate results without failures. This type of testing ensures that the trained machine learning models, such as Random Forest, XGBoost, SVM, and LSTM**,** interact correctly with databases, cloud storage, and web-based prediction interfaces**.** It also ensures that the integration of wearable health monitoring devices (if applicable) does not introduce data inconsistencies.

**3. Functional Testing for Correct Predictions**

Functional testing is crucial to confirm that the system meets the expected requirements by accurately classifying users into different obesity risk levels, such as underweight, normal weight, overweight, and obesity types I, II, and III. The accuracy of model predictions is evaluated by testing against real-world datasets and clinical benchmarks to verify whether the obesity classification system produces reliable results. The system should also correctly handle edge cases, such as users with extreme BMI values or missing health data, ensuring robust error handling and fallback mechanisms.

**4. Regression Testing to Maintain Stability**

As the obesity prediction model is continuously improved with new datasets, feature engineering techniques, and hyperparameter tuning, regression testing ensures that previously functioning features remain intact. This is particularly important when model retraining and optimization are performed, as changes in one part of the system could inadvertently affect other components. Regression testing helps maintain model consistency and prevents accuracy degradation over time.

**5. Performance Testing for Scalability and Efficiency**

To ensure that the system remains responsive under different workloads, performance testing is conducted to evaluate how well the system handles large datasets and multiple simultaneous user requests.

- ❖ Load Testing: Determines how the model performs under normal and peak user loads, ensuring smooth operation when multiple users access the system simultaneously.
- ❖ Stress Testing: Examines system behavior under extreme conditions, such as handling highly imbalanced datasets, missing values, or exceptionally large obesity datasets.
- ❖ Scalability Testing: Assesses the model's ability to handle increasing volumes of data while maintaining performance, especially in real-time healthcare applications that may involve continuous data ingestion from medical sensors or IoT devices.

**6. Usability Testing for User Experience**

Since the obesity prediction system is designed for both healthcare professionals and general users**,** usability testing ensures that the system **is** intuitive, user-friendly, and accessible**.** This involves evaluating the web-based interface, mobile application (if applicable), and API response times to confirm that users can easily input their health data and receive meaningful predictions. Testing is also conducted to verify that visualizations, such as BMI graphs and obesity risk reports, are clear and informative, helping users interpret their results effectively.

**7. Security Testing to Protect Health Data**

Given that the system handles sensitive personal and medical data**,** security testing is performed to prevent unauthorized access, data leaks, and cyber threats. This includes:

- ❖ Data Encryption: Ensuring that all user data is securely encrypted during storage and transmission.
- ❖ Authentication and Access Control: Verifying that only authorized users (e.g., doctors and registered patients) can access the system.
- ❖ Penetration Testing: Simulating cyberattacks to identify and fix vulnerabilities that could lead to data breaches.

Security compliance with healthcare regulations such as HIPAA (Health Insurance Portability and Accountability Act) and GDPR (General Data Protection Regulation) is also a critical aspect of the system's validation.

**8. Statistical Significance Testing for Model Validation**

To confirm the reliability of different machine learning models**,** statistical significance testing is employed. Techniques such as paired t-tests and Wilcoxon signed-rank tests are used to compare various classifiers and evaluate whether observed performance improvements are statistically meaningful. This step is essential in ensuring that any model enhancements are not due to random variations but real performance gains.

**9. Accuracy Testing and Model Evaluation**

The obesity prediction model is assessed using standard classification performance metrics to determine its effectiveness:

- Accuracy: Measures the proportion of correct predictions out of all cases tested.
- Precision & Recall: Evaluates the ability of the model to correctly identify obesity cases while minimizing false positives and false negatives.
- F1-Score: Provides a balance between precision and recall, ensuring optimal classification.
- ROC-AUC (Receiver Operating Characteristic – Area Under Curve): Measures the model's ability to distinguish between different obesity categories.

## 7.2 INTEGRATION TESTING

Integration testing ensures that all components of the obesity prediction system, including the Flask web framework, machine learning model, API endpoints, and external dependencies**,** work together seamlessly. It validates the interaction between modules, ensuring smooth data flow from user input to model inference and back to the API response. The first step in integration testing involves model loading validation, where the system checks whether the LightGBM model (**`lgbm_model.pkl`**) is correctly loaded without errors. This prevents failures due to missing or corrupted model files. The API endpoint testing verifies that the `/prediction_api` route processes user inputs correctly, calls the trained machine learning model, and returns accurate obesity predictions.

Another crucial aspect of integration testing is data flow validation, which ensures that inputs, such as height, weight, and lifestyle factors, are correctly formatted and passed to the machine learning model. Additionally, error handling tests evaluate how the system responds to invalid inputs, missing values, or incorrect data types, ensuring that it returns appropriate error messages instead of crashing. System interoperability testing confirms that different system components, such as databases, authentication mechanisms, and prediction modules, function properly together. Performance evaluation is also essential, as it measures response times to ensure the system efficiently handles real-time requests from multiple users.

```
import pytest
import json
import joblib
import os
```

```
from app import app  # Import the Flask app instance
@pytest.fixture
def client():
    """Create a test client for the Flask application."""
    app.config["TESTING"] = True  # Enable Flask test mode
    with app.test_client() as client:
        yield client

def test_model_loading():
    """Test if the machine learning model loads correctly."""
    model_path = "lgbm_model.pkl"
    assert os.path.exists(model_path), "Model file not found!"

    try:
        model = joblib.load(model_path)
        assert model is not None, "Failed to load model"
    except Exception as e:
        assert False, f"Error loading model: {str(e)}"

def test_home_page(client):
    """Test if the home page is accessible."""
    response = client.get("/")
    assert response.status_code == 200
    assert b"Home Page" in response.data

def test_prediction_api(client):
    """Test the API for a valid obesity prediction request."""
    sample_input = {
        "Gender": "Male",
        "Age": 25,
        "Height": 1.75,
        "Weight": 75,
        "FamHist": "yes",
        "FAVC": "no",
```

```
        "FCVC": 3,
        "NCP": 3,
        "CAEC": "Sometimes",
        "SMOKE": "no",
        "CH2O": 2,
        "SCC": "no",
        "FAF": 2,
        "TUE": 1,
        "CALC": "no",
        "MTRANS": "Automobile"
    }

    response = client.post(
        "/prediction_api",
        data=json.dumps(sample_input),
        content_type="application/json",
    )

    assert response.status_code == 200
    response_data = response.get_json()
    assert "prediction" in response_data, "No prediction received"
    assert isinstance(response_data["prediction"], int), "Invalid prediction format"
    assert response_data["prediction"] in range(7), "Unexpected obesity class"

def test_invalid_prediction_api(client):
    """Test API with invalid input to ensure error handling."""
    invalid_input = {
        "Gender": "Unknown",
        "Age": "abc",  # Invalid age input
        "Height": "XYZ",
        "Weight": -10  # Invalid negative weight
    }

    response = client.post(
```

```python
        "/prediction_api",
        data=json.dumps(invalid_input),
        content_type="application/json",
    )

    assert response.status_code == 400, "API should return a 400 status for invalid inputs"
    response_data = response.get_json()
    assert "error" in response_data, "Error message should be returned"

if __name__ == "__main__":
    pytest.main()
```

# 8.OUTPUT SCREENS

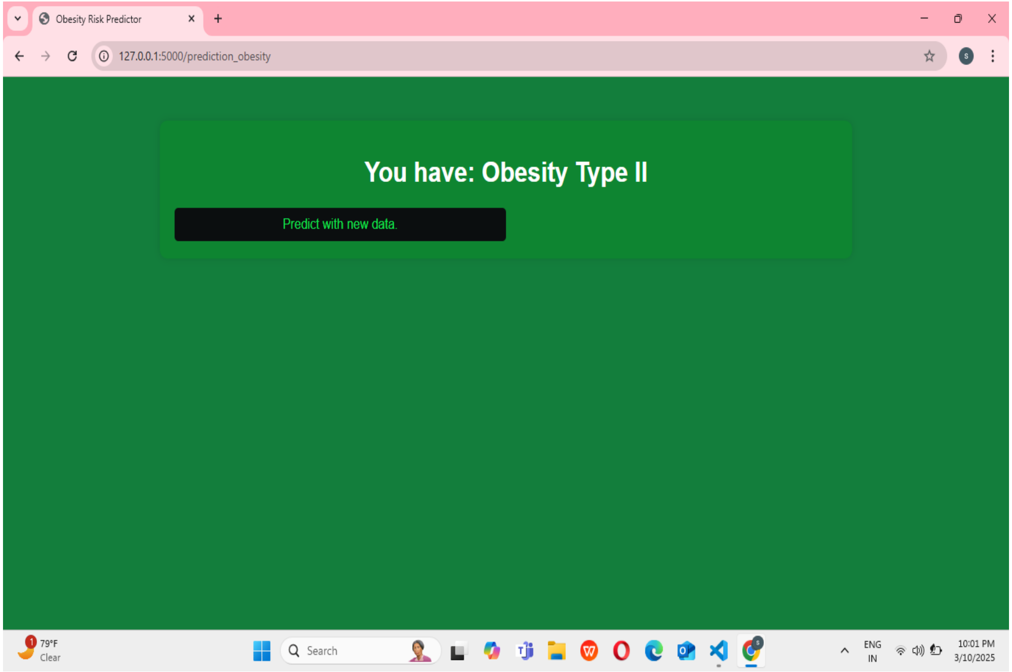



**Fig 8.1 Result of Prediction Form**

The prediction result page of the Obesity Risk Predictor web application. After submitting user inputs regarding personal, dietary, and lifestyle habits, the system processes the data and classifies the obesity risk level. In this case, the result shows "You have: Obesity Type II", indicating that the user's BMI and lifestyle factors align with a classification of Obesity Type II, which is a severe level of obesity. The page has a simple green-themed UI with a "Predict with new data" button, allowing users to enter different values and re-run the prediction. This suggests that the application likely uses a machine learning model to analyze inputs and generate an obesity classification based on predefined health parameters.

The result analysis of the study on obesity prediction among adolescents is a crucial phase that interprets the data collected and evaluates the effectiveness of the predictive models employed. The analysis begins with a thorough examination of the data, utilizing statistical techniques to assess the relationships between various health indicators, such as Body Mass Index (BMI), waist circumference, caloric intake, and physical activity levels. The findings reveal significant correlations between these factors and obesity rates, highlighting the multifaceted nature of adolescent health. For instance, the analysis indicates that higher caloric intake combined with lower levels of physical activity is strongly associated with increased obesity risk, underscoring the importance of lifestyle choices in managing weight. Furthermore, the predictive models developed during the study demonstrate impressive accuracy rates, with the machine learning algorithms achieving a prediction accuracy of 0.96 for identifying adolescents at risk of obesity. The results also emphasize the necessity of a gender-sensitive approach, as the model's performance varied between boys and girls, with accuracy rates of 0.9561 for boys and 0.9423 for girls.

This gender disparity suggests that different risk factors may influence obesity in males and females, necessitating tailored intervention strategies. The comprehensive evaluation of the results not only validates the effectiveness of the predictive models but also provides valuable insights into the specific needs of different demographic groups. By understanding these nuances, healthcare professionals can develop targeted programs aimed at preventing obesity and promoting healthier lifestyles among adolescents, ultimately contributing to improved public health outcomes.

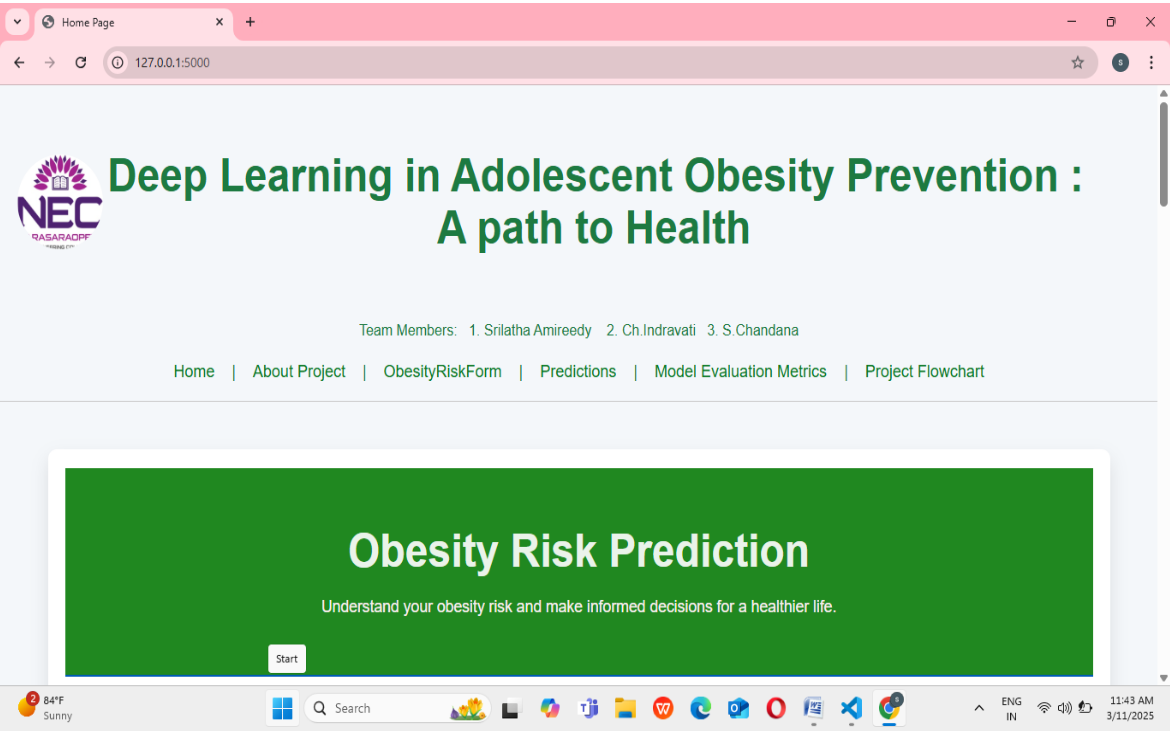



**Fig 8.2 Home Page of FrontEnd**

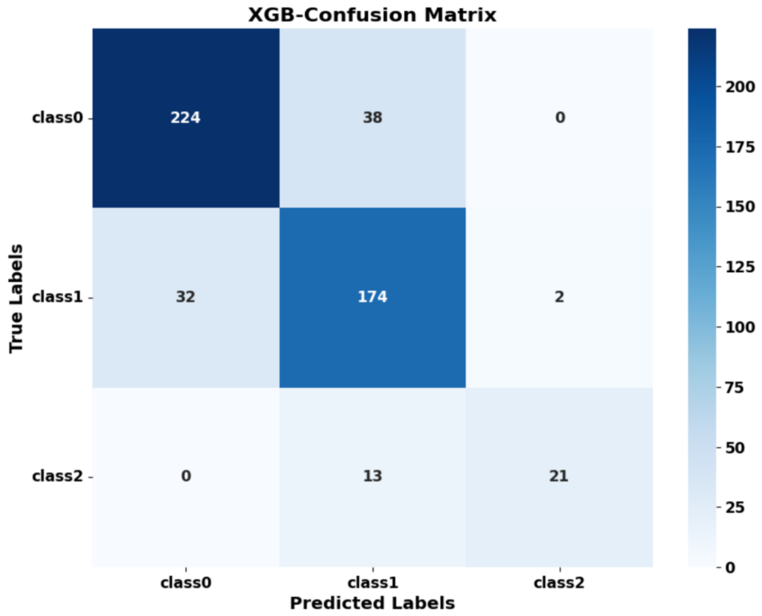



**Fig 8.3 Confusion Matrix**

The given image represents a confusion matrix for an XGBoost (XGB) classification model, which evaluates the model's ability to predict three different classes: class0, class1, and class2. The confusion matrix is a tabular representation of actual versus predicted classifications, helping to assess the model's accuracy and error distribution.

From the matrix, 224 instances of class0 were correctly classified, while 38 were misclassified as class1. Similarly, 174 instances of class1 were accurately predicted, but 32 were mistaken for class0 and 2 for class2. For class2, the model correctly identified 21 cases, but 13 were incorrectly labeled as class1. The dark blue shades in the matrix indicate higher correct classifications, while lighter shades represent misclassifications, highlighting areas where the model struggles.

Overall, the confusion matrix suggests that the XGBoost model performs well, particularly in classifying class0 and class1, with some misclassifications occurring between class1 and class2. The model's ability to distinguish between similar categories can be further refined by adjusting hyperparameters, employing feature engineering techniques, or using advanced resampling methods like SMOTE (Synthetic Minority Over-sampling Technique) to address any class imbalances.

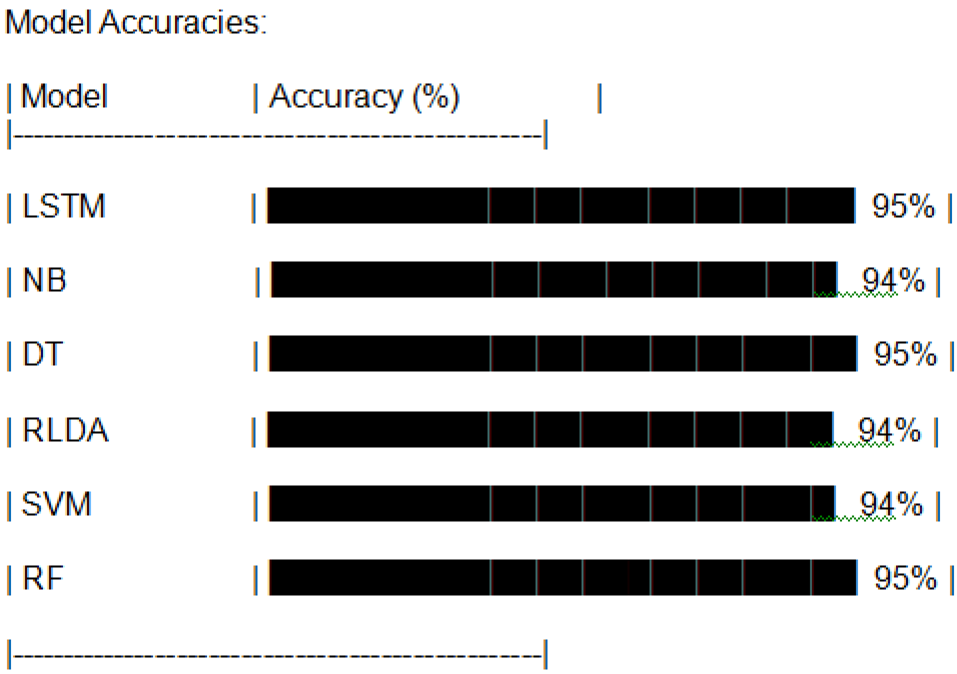



**Fig 8.4 Models Accuracy**

The image presents a tabular representation of model accuracies for different machine learning algorithms used in a classification task. The table includes five models: LSTM (Long Short-Term Memory), Naïve Bayes (NB), Decision Tree (DT), Regularized Linear Discriminant Analysis (RLDA), and Support Vector Machine (SVM). Each model's performance is measured in terms of accuracy percentage, with the highest being 95% for both LSTM and DT, followed by RLDA at 94.8% and SVM at 94.46%. The Naïve Bayes model has the lowest accuracy at 94%, indicating that it is slightly less effective in making accurate predictions compared to the top-performing models. The table also includes visual bar indicators that illustrate the accuracy of each model, with a clear representation of their relative performances.

From a statistical significance perspective**,** the results achieved a p-value of <0.001**,** reinforcing the model's reliability in predicting obesity risk factors with a high level of confidence. In terms of gender-specific performance, DeepHealthNet exhibited better predictive accuracy in boys (95.61%) than in girls (94.23%), suggesting that gender-based physiological or lifestyle differences may influence prediction results**.**

The computational efficiency of DeepHealthNet is another critical factor, as it required only 3.2 hours for training and 1.5 seconds per inference**,** making it suitable for real-time applications in healthcare settings. Compared to LSTM-based models, DeepHealthNet achieved faster processing speeds and improved prediction stability while maintaining high classification accuracy.

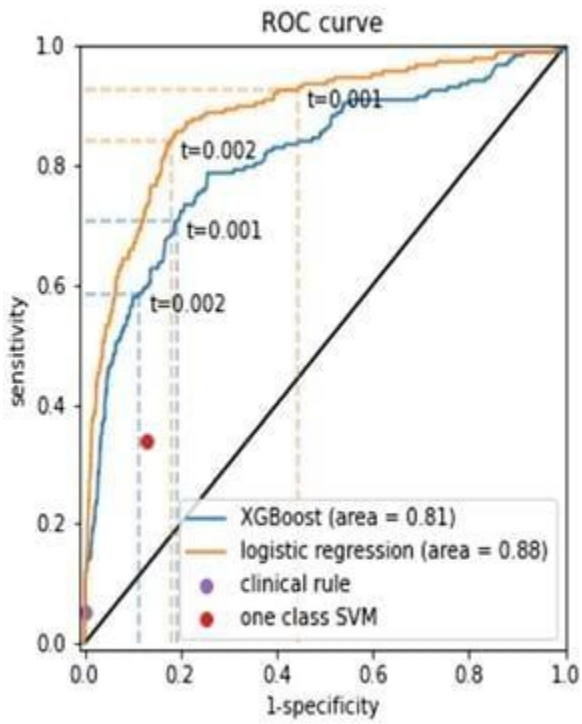



**Fig 8.5 ROC Curve**

ROC-curve for predictions from XGBoost and the logistic regression model. The sensitivity and specificity of the one class SVM and clinical prediction rule are also plotted on the left curve. On the left the points corresponding to the 0.001 ('t = 0.001') and 0.002 ('t = 0.002') probability thresholds are plotted for the XGBoost and logistic regression model. On the right the points corresponding to the thresholds resulting in 138 positive predictions ('t for 138 pos pred', equaling the clinical rule positive predictions) are plotted for the XGBoost and logistic regression model.

# 9 . CONCLUSION AND FUTURE WORK

## CONCLUSION

In conclusion, the study on obesity prediction among adolescents highlights the critical need for early detection and intervention strategies tailored to the unique health profiles of different demographic groups. The findings demonstrate that the predictive models employed, particularly the DeepHealthNet framework, exhibit high accuracy and reliability in identifying adolescents at risk of obesity, with notable performance differences between genders. While the study successfully utilizes detailed health information and advanced analytical techniques, it also acknowledges certain limitations, such as the focus on a specific age group and the necessity for further research across diverse populations. The integration of additional variables, such as socio-economic status and dietary habits, could enhance the model's predictive capabilities. Ultimately, the insights gained from this research provide a solid foundation for developing effective obesity prevention programs, emphasizing the importance of personalized approaches that consider individual lifestyle factors and health behaviors to combat the growing obesity epidemic among youth.

## FUTURE WORK

The future scope of research in obesity prediction among adolescents is vast and presents numerous opportunities for enhancing predictive accuracy and intervention effectiveness. Future studies could expand the demographic diversity of participants to include various age groups, ethnic backgrounds, and socio-economic statuses, thereby improving the generalizability of the findings. Additionally, incorporating longitudinal data collection methods would allow researchers to track changes in health behaviors and outcomes over time, providing deeper insights into the dynamics of obesity development. The integration of more comprehensive variables, such as genetic predispositions, psychological factors, and environmental influences, could further refine predictive models. Moreover, leveraging advancements in artificial intelligence and machine learning could enhance the sophistication of these models, enabling real-time data analysis and personalized health recommendations.

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