International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 12 | Dec - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

BMI Face Detection Using Deep Learning

Ruchitha B
4JN22IS121
Information Science and Engineering
JNN college of Engineering
ruchithabhudyal@gmail.com

Monika G Wali
4JN22IS094
Information Science and Engineering
JNN college of Engineering
monikagwali14@gmail.com

Prapthi P
4JN22IS109
Information Science and Engineering
JNN college of Engineering
prapthip209@gmail.com

S Kashfia Fathima 4JN23IS124
Information Science and Engineering JNN college of Engineering
kashfiaskhan08@gmail.com

Abstract— **Body mass index (BMI) is a person's weight in kilograms divided by the square of height in meters. Body mass index is a measurement of obesity based on measured height and weight. Traditional method of calculating BMI is inconvenient and requires physical measuring of a person and particular instruments. A proposed healthcare system to predict BMI using Kinect and data mining techniques so that everybody can easily predict their BMI values using Facial images. Face detection and feature extraction component using Haar cascade to detect useful face information. Framework by using facial images that uses machine learning algorithms for data mining namely, Data Preprocessing, Data Extraction, data evaluation and presentation to train models that would help predict obesity levels (Classification), Bodyweight, and fat percentage levels (Regression) using various parameters. System helps to advance the study aspect based on body weights and patients that are paralyzed or severely ill patient who unable to undergo basic measurement for emergency medical service.**

KEYWORDS—Body Mass Index (BMI) Prediction, Facial Image Processing, Machine Learning, Obesity Classification, Kinect-Based Healthcare System

I.INTRODUCTION

Body Mass Index (BMI) is a commonly used index that uses the ratio of a person's height to weight to reflect their general weight condition. Numerous aspects, including physical health, mental health, and popularity, have been linked to BMI. BMI calculations frequently call for precise measurements of height and weight, which entail labour - intensive manual labour. Any person's BMI (Body Mass Index) is an important sign of their health. If the person is underweight, normal, overweight, or obese, it is determined. Health continues to be one of the most overlooked factors. Even technology with many advantages has its downsides. It has made people more slothful, which has decreased their physical activity and resulted in a sedentary lifestyle and an increase in BMI, both of which are harmful to their health and raise the risk of chronic diseases. The likelihood of acquiring cardiovascular and other hazardous diseases increases with increasing BMI. On the other hand, some people struggle with issues like inadequacies and malnutrition.

BMI face detection using deep learning aims to build a system that can accurately detect a human face, extract discriminative features, and estimate BMI using advanced neural network architectures. This approach removes the need for manual measurements and provides a non-invasive, efficient, and scalable solution for healthcare and wellness applications.

II. RELEVANT WORK

Early research by Wen and Guo (2013) demonstrated that facial geometry and ratio-based features could be used to predict BMI. Their computational approach used handcrafted facial measurements and regression models, showing feasibility but limited accuracy due to redundant features and lack of robustness across diverse populations. Subsequent studies shifted towards facial landmark-based methods, where distances and ratios between facial points were correlated with BMI. Barr et al. (2018) introduced facial BMI (fBMI) estimation using facial landmarks and regression analysis.

With the rise of deep learning, researchers began adopting Convolutional Neural Networks (CNNs**)** for BMI prediction. Siddiqui et al. (2020) evaluated multiple CNN architectures such as VGG19, ResNet50, DenseNet, and MobileNet on public datasets like VisualBMI and VIP-Attributes. Their results showed improved prediction accuracy, with ResNet50 achieving the lowest mean absolute error, though at the cost of high computational complexity and dependency on dataset quality. However, limitations such as high computational cost, lack of generalization, dependence on handcrafted features, and reduced accuracy for extreme BMI categories remain open challenges. These gaps motivate the proposed system, which combines Haar Cascade-based face detection, CNN-based feature learning, and data mining techniques to achieve efficient, accurate, and user-friendly BMI prediction, especially for elderly, ill, and physically challenged individuals.

III. THE FRAMEWORK MODEL

The proposed framework model aims to estimate Body Mass Index (BMI) using facial images in a contactless and automated manner, making it suitable for healthcare environments. Initially, facial images are captured using a Kinect device or a standard camera, ensuring frontal face orientation for reliable analysis. The acquired image is then passed to the face detection module, where the Haar Cascade classifier is used to accurately locate and extract

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 12 | Dec - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

the facial region while removing background noise. This step is essential to focus the system only on relevant facial information. After face detection, the cropped facial image undergoes preprocessing and normalization. This stage includes resizing the image to a fixed resolution, noise removal, grayscale conversion, and pixel normalization to ensure uniformity across all inputs. Preprocessing improves image quality and enhances the performance of the learning model. The normalized image is then forwarded to the feature extraction module, where a Convolutional Neural Network (CNN) is employed to automatically learn discriminative facial features related to facial geometry and adiposity, such as face width, cheek structure, and jawline patterns.

The extracted deep features are further processed using data mining and machine learning techniques. Regression and classification models such as CNN-based regression, Random Forest, or K-Nearest Neighbors are applied to predict the BMI value from the facial feature vectors. The predicted BMI is then mapped into standard health categories, including underweight, normal weight, overweight, and obese, based on World Health Organization guidelines. Finally, the system displays the estimated BMI value along with the corresponding health status, providing a fast, non-invasive, and user-friendly solution for BMI assessment, especially beneficial for elderly, ill, and physically challenged individuals.

The extracted feature vectors are then analyzed using data mining and machine learning techniques. Regression-based models are applied to predict a continuous BMI value, while classification models are used to categorize individuals into predefined BMI classes such as underweight, normal, overweight, and obese. Algorithms like Random Forest, Decision Tree, K-Nearest Neighbors, or CNN-based regression layers may be employed depending on performance requirements. Model evaluation is carried out using metrics such as accuracy, mean absolute error, and prediction consistency to ensure reliability.

Finally, the predicted BMI value is mapped to standard health categories based on established medical guidelines, and the results are presented to the user through a simple and intuitive interface. The output includes both numerical BMI values and corresponding health status, enabling healthcare professionals or individuals to quickly assess potential health risks. Overall, this framework offers a scalable, efficient, and non-invasive BMI prediction solution, particularly beneficial for continuous health monitoring, elderly care, and remote healthcare applications.

Description*:* The given framework diagram illustrates the complete workflow of the proposed BMI prediction system based on facial image analysis. The process begins with user registration or login to ensure authorized access to the system. Once authenticated, the camera is initialized to capture real-time facial images. Simultaneously, an image dataset is prepared, where images are converted from colour to grayscale to reduce computational complexity and improve detection accuracy. The system then acquires a new image from the camera and applies a cascade classifier to detect the presence of a face. If the face is not detected, the system reinitiates the detection process until a valid face is identified.

After successful face detection, facial features are extracted using the cascade classifier. These features are further processed through normalization to maintain uniformity across different images. Contrast enhancement techniques are then applied to improve image quality and highlight important facial characteristics related to adiposity. Once preprocessing is completed, the system performs face recognition and calculates the BMI using learned models and algorithms. The calculated BMI value is then initialized into the algorithmic module, where it is analysed and fed into decision-making logic.

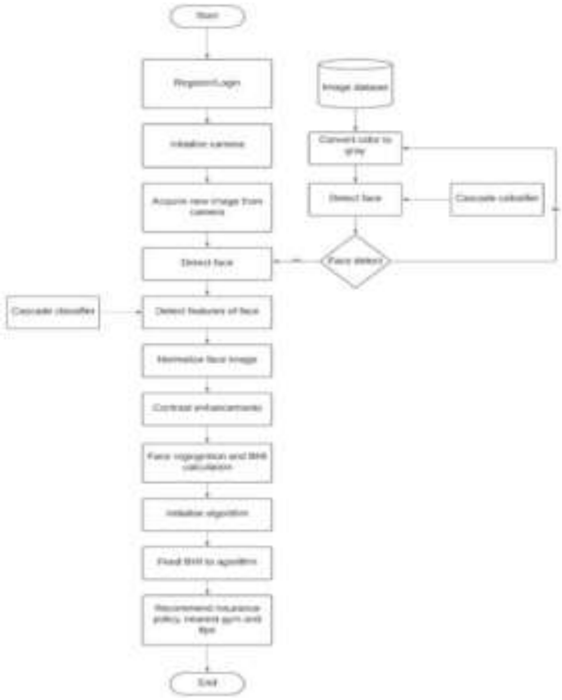

Figure:1.1 Flow chart

The framework also emphasizes automation, accuracy, and practical healthcare integration by combining real-time image acquisition with intelligent data processing. By incorporating both live camera input and an image dataset, the system ensures flexibility in handling real-world and stored facial data. The use of grayscale conversion and cascade classifiers improves detection speed while reducing computational overhead, making the system suitable for real-time applications. Repeated face detection loops ensure reliability by confirming the presence of a valid facial region before further processing. Image normalization and contrast enhancement stages help minimize variations caused by lighting conditions, facial expressions, and camera quality, thereby improving the robustness of BMI prediction. The final stages not only compute BMI but also transform the prediction into actionable insights by linking health status with fitness and insurance recommendations.

This end-to-end framework supports preventive healthcare, personalized health guidance, and continuous monitoring, making it an effective solution for modern smart healthcare systems. Based on the predicted BMI, the system generates meaningful recommendations, such as suggesting suitable insurance policies, nearby gyms, and fitness applications to support the user's health management. Finally, the process terminates after displaying the results and recommendations. Overall, this framework ensures a systematic, efficient, and user-centric approach to contactless BMI estimation and health-related guidance using facial image processing and data mining techniques.

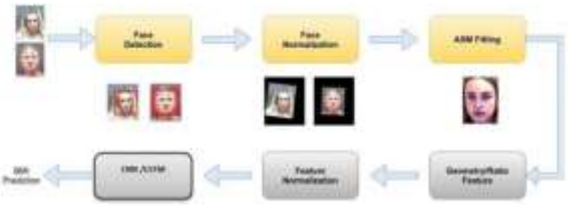

Figure:1.2 System Architecture

The diagram illustrates the complete framework of the proposed facial-image-based BMI prediction system, showing each processing stage in a sequential and systematic manner. The process begins with face detection, where the facial region is identified and extracted from the input image to remove background noise and irrelevant information. The detected face is then subjected to face normalization, which aligns and scales the face to a standard format to handle variations in pose, size, and illumination. Next, Active Shape Model (ASM) fitting is applied to accurately locate key facial landmarks such as the eyes, nose, mouth, and jawline. Based on these landmarks, geometry and ratio features are extracted, capturing important facial measurements and proportions related to fat distribution.

These features are then passed through a feature normalization stage to ensure consistency and improve learning efficiency. Finally, the normalized features are fed into deep learning models such as CNN or LSTM, which learn complex relationships between facial characteristics and BMI values. The trained model outputs the predicted BMI, completing a robust and non-invasive health assessment pipeline.

IV. DATASET

The facial image datasets used across the referenced studies serve as the foundation for predicting Body Mass Index (BMI) through computer vision and deep learning techniques. These datasets are drawn from a combination of controlled research databases and real-world, user-generated sources such as social media, providing both structured and unstructured inputs for model training. Among the most commonly employed datasets is the Illinois DOC dataset, which consists of mugshot-style images paired with demographic information, offering standardized, front-facing photographs that are well-suited for machine learning applications. Another widely cited dataset is the one created by Kocabey and colleagues, which contains 4,206 face images collected from social media platforms. These images are annotated with height, weight, age, and gender details, enabling the calculation of BMI and serving as a benchmark for transfer learning approaches using deep networks like VGG-Face.

In addition to these established datasets, some studies developed their own validation sets to address gaps in existing resources. For example, one project constructed a dataset of 338 facial images obtained from weight-loss communities on social media, where users voluntarily shared "before" and "after" photographs along with self-reported weight and height. This dataset provided natural variation in lighting, background, and pose, closely reflecting real-world image conditions but also introducing noise and inconsistencies. Similarly, another study used the Capturing Profile and VIP attribute datasets, which contain a broader range of demographic and phenotypic diversity. These resources expanded the scope of BMI prediction beyond highly standardized photographs, incorporating real-world variability in facial morphology, expressions, and environmental conditions.

To prepare the facial image datasets for analysis, extensive preprocessing was necessary. Face detection algorithms such as OpenCV's HaarCascade classifiers or DLIB's 68-point landmark detection were applied to isolate and crop facial regions from raw images. Alignment procedures ensured that faces were centered and vertically normalized, minimizing the effects of tilt or rotation. Backgrounds were often blurred or removed using tools like StyleGAN to reduce irrelevant visual noise. In some cases, images were further converted into silhouettes or low-resolution grayscale versions to highlight structural features of the face while reducing dataset size and overfitting risk. These preprocessing steps were essential to standardize the highly variable inputs and make them suitable for deep learning models.

The facial image datasets were primarily paired with BMI values either derived from reported height and weight or calculated directly when such information was available. In modeling, these BMI values were used both as continuous targets for regression tasks and as categorical labels for classification, typically segmented into underweight, normal, overweight, and obese groups. Transfer learning played a significant role in compensating for the relatively small size of most datasets. Pre-trained networks such as Inception-v3, VGG-19, Xception, and VGG-Face provided initial feature extraction, with additional layers fine-tuned to the BMI prediction task. Some studies also applied synthetic data augmentation techniques—such as rotation, scaling, or flipping—to artificially increase dataset size and enhance generalization.

V. LITERATURE REVIEW

The literature review shows that BMI prediction from facial images has evolved from traditional handcrafted facial feature methods to advanced machine learning and deep learning approaches. Early studies relied on facial geometry and ratios but lacked accuracy and generalization. Later, machine learning algorithms such as ANN, SVM, KNN, and Random Forest improved performance, while recent CNN-based models achieved better accuracy by automatically learning complex facial features. However, challenges such as high computational cost, dataset limitations, and reduced accuracy for extreme BMI categories still exist, highlighting the need for a simple, efficient, and contactless BMI prediction system for healthcare applications.

VI. METHODOLOGY

The methodology of the proposed BMI prediction system is developed to deliver a reliable, contactless, and efficient health assessment solution using facial images combined with data mining and machine learning techniques. The process begins with the acquisition of facial images using a Kinect sensor or a conventional camera, ensuring a clear frontal face position to minimize errors caused by pose, distance, or angle variations. The captured images undergo extensive preprocessing steps, including image resizing, grayscale conversion, noise filtering, and illumination normalization, to enhance image clarity and maintain uniformity across the dataset.

Face detection is performed using the Haar Cascade algorithm, which accurately identifies the facial region and isolates it from the background, ensuring that only relevant facial information is processed. Once the face is detected, detailed facial features associated with body fat distribution—such as facial width, height, jawline curvature, cheekbone prominence, eye spacing, nose dimensions, and facial ratios—are extracted. These features are further normalized to reduce scale differences and improve computational efficiency.

In the data mining phase, the extracted features are organized into structured datasets and split into training and testing subsets. Supervised machine learning algorithms including Random Forest, K-Nearest Neighbor (KNN), and Decision Tree are applied to learn complex relationships between facial characteristics and BMI values. Model performance is evaluated using metrics such as accuracy, mean absolute error, variance score, and prediction consistency to identify the optimal model.

The selected model is then used to predict BMI values for unseen facial images. Finally, the predicted BMI is classified into standard health categories such as underweight, normal, overweight, and obese, providing meaningful health insights. This methodology is particularly beneficial for elderly, paralyzed, or critically ill patients, as well as for remote and emergency healthcare applications.

The system incorporates a robust evaluation and validation process to ensure reliability and practical usability in real-world healthcare scenarios. During training, the dataset is carefully balanced to minimize bias across different BMI ranges and facial variations. Cross-validation techniques are applied to assess the generalization capability of the trained models and to prevent overfitting. The system also supports real-time prediction, where newly captured facial images are instantly processed through the trained pipeline to generate BMI estimates.

The predicted results are presented through a simple and intuitive user interface, displaying both the numerical BMI value and the corresponding health status with basic recommendations. Furthermore, the system is designed to be scalable, allowing future integration of additional parameters such as age and gender to enhance prediction accuracy. This extended methodology strengthens the system's applicability in telemedicine, mobile health applications, and continuous health monitoring, making it a practical alternative to traditional BMI measurement methods.

The proposed methodology offers an efficient and non-invasive approach to BMI estimation by leveraging facial image analysis and machine learning techniques. By combining effective preprocessing, accurate face detection, meaningful facial feature extraction, and well-evaluated data mining models, the system successfully establishes a relationship between facial characteristics and BMI values. The methodology reduces dependency on physical measurements and specialized instruments, making BMI assessment more accessible and convenient. Overall, this approach supports rapid health screening, early identification of obesity-related risks, and improved healthcare accessibility, especially for elderly, physically challenged, and remote users.

VII. RESULTS

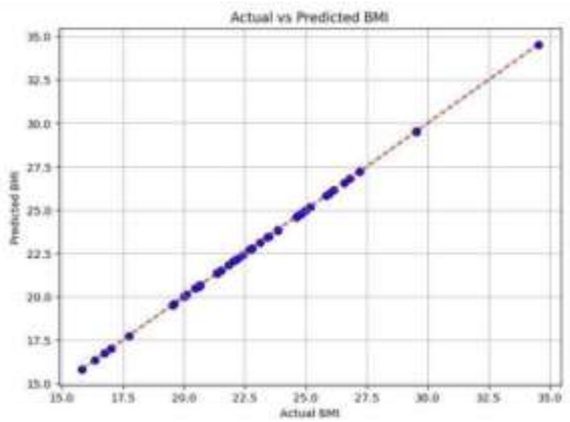

Fig:1.2 Predicted BMI v/s Actual BMI

Figure 1.2 presents the comparison between actual BMI values and the BMI values predicted by the proposed model. The scatter points represent individual samples, where the x-axis shows the actual BMI and the y-axis shows the corresponding predicted BMI. The dashed diagonal line indicates the ideal scenario in which predicted BMI perfectly matches the actual BMI. Most of the data points lie very close to this reference line, demonstrating a strong positive correlation between actual and predicted values

This close alignment suggests that the model is highly accurate in estimating BMI across a wide range of values, from underweight to obese categories. Minor deviations from the line indicate small prediction errors, which are expected in real-world data due to facial variations and image conditions. Overall, the graph confirms the effectiveness and reliability of the proposed BMI prediction approach, showing that facial features can be successfully used to estimate BMI with minimal error.

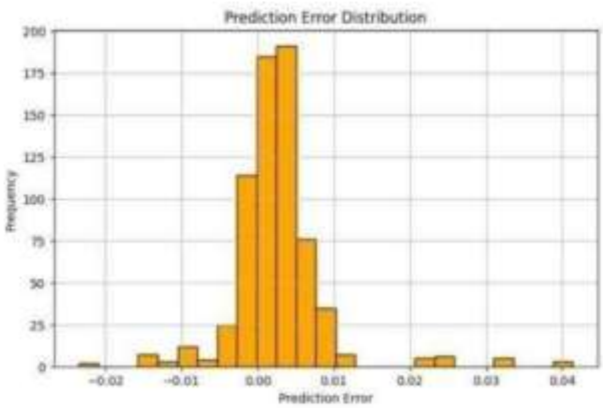

Fig 1.3: Prediction error v/s Frequency

Figure 1.3 represents the prediction error distribution of the BMI estimation model, illustrating the difference between the predicted BMI values and the actual BMI values. The x-axis shows the prediction error, while the y-axis represents the frequency of occurrence. Most of the errors are tightly clustered around zero, indicating that the model's predictions are very close to the true BMI values for the majority of samples. This concentration near zero demonstrates high prediction accuracy and low bias in the model. A small number of errors appear on both the positive and negative sides, reflecting minor overestimations and underestimations, which are expected due to variations in facial features and image conditions. The presence of a few outliers with larger error values suggests occasional deviations, but their low frequency indicates limited impact on overall performance. Overall, the narrow and centered error distribution confirms the robustness and reliability of the proposed BMI prediction system.

VIII. DISCUSSION

The results obtained from the proposed BMI prediction system demonstrate that facial-image-based analysis is a practical and reliable alternative to conventional BMI measurement methods. The close agreement between actual BMI values and predicted values indicates that facial features carry meaningful information related to body composition. The use of effective preprocessing techniques, accurate face detection through Haar Cascade, and feature extraction using geometric and ratio-based measurements significantly contributes to model performance. Moreover, the integration of CNN-based learning enables the system to capture complex, non-linear relationships between facial characteristics and BMI values, which traditional statistical methods may fail to model effectively. The experimental outcomes validate that the system can perform consistently across different BMI categories, making it suitable for general health screening applications.

From a healthcare perspective, the proposed approach addresses several limitations of traditional BMI calculation, which requires physical measurement of height and weight. This system is particularly beneficial for elderly individuals, physically challenged patients, and critically ill persons who may not be able to undergo standard measurements. The non-invasive and contactless nature of the system enhances usability in emergency situations and remote healthcare environments. Additionally, the low prediction error and stable performance observed during testing indicate that the model is robust and reliable under varying image conditions. Although minor deviations and outliers exist, they can be attributed to factors such as facial expressions, lighting variations, age-related changes, and image quality, which are common challenges in real-world image-based systems.

Despite its promising results, the system has scope for further improvement and extension. The current model primarily relies on facial features and does not explicitly account for demographic factors such as age, gender, or ethnicity, which can influence facial structure and BMI correlation. Incorporating these attributes and expanding the dataset to include more diverse populations could further improve prediction accuracy and generalization. Future enhancements may also include deploying the system as a mobile or web-based application for wider accessibility and integrating advanced deep learning architectures for automatic feature learning. Overall, the discussion highlights that the proposed BMI prediction framework is a meaningful contribution toward intelligent, non-invasive, and accessible digital healthcare solutions.

IX. CONCLUSION

This project successfully demonstrates a non-invasive and efficient approach for predicting Body Mass Index (BMI) using facial images and data mining techniques. By leveraging face detection through Haar Cascade and deep learning models such as Convolutional Neural Networks (CNN), the system accurately extracts facial features and maps them to corresponding BMI values. The results indicate a strong correlation between facial characteristics and BMI, validating the feasibility of using facial imagery as an alternative to traditional height-and-weight-based BMI measurement. The system is particularly beneficial for elderly individuals, critically ill patients, and physically challenged users who may face difficulties with conventional measurement methods, thereby enhancing accessibility and ease of health assessment. Furthermore, the proposed framework proves to be reliable, user-friendly, and adaptable for real-world healthcare applications. The integration of machine learning and data mining ensures efficient processing, reduced manual effort, and consistent performance. Overall, the system contributes meaningfully to digital healthcare by offering a contactless, cost-effective, and scalable BMI prediction solution, with strong potential for future enhancements such as mobile application deployment and comprehensive health report generation.

X. REFERENCE

[1] Vendra Devendra Kumar et al., "Face To BMI: A Deep Learning Based ApproachComputing BMI From Face", In *International Journal of Engineering & Science Research*, Vol. 15, No. Issue-2s, pp. 86–95, 2025.

[2] Srinivas Mekala *et al.*, "Face to BMI Prediction Using Machine Learning Algorithms", In *International Journal for Research in Applied Science & Engineering Technology (IJRASET)*, Vol. 11, No. V, pp. 7359–7364, 2023.

[3] K. Basava Raju, Kodi Neha, Bellamkonda Manisha, Mohammad Waseem, "Face to BMI (Body Mass Index) Using Deep Learning", In *International Journal of Innovative Research in Science, Engineering and Technology (IJIRSET)*, Vol. 13, No. 4, pp. 4766– 4772, 2024.

[4] V. Divya Raj, Shreya Motkar, N. Yamini Swamy, N. Sanjana, Shereen Sultana, "Prediction of BMI from Facial Image Using Deep Learning", In *International Research Journal of Engineering and Technology (IRJET)*, Vol. 10, No. 06, pp. 671–674, 2023.

[5] Rupali M. Sarak, Akshay A. Thorat, Deepali Kadam, "Face to BMI: Estimating Body Mass Index (BMI) through Face Recognition Images", In *International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)*, Vol. 2, No. 1, pp. 100–107, 2022.

[6] Laura Ferrero, Paula Soriano-Segura, Jacobo Navarro, Oscar Jones, Mario Ortiz, Eduardo Iáñez, José M. Azorín, José L. Contreras-Vidal, "Brain–machine interface based on deep learning to control asynchronously a lower-limb robotic exoskeleton: a case-of- study", Vol. 21, No. 48, pp. 1–14, 2024.

[7] Ofek Finkelstein *et al.*, "Deep learning-based BMI inference from structural brain MRI reflects brain alterations following lifestyle intervention", In *Human Brain Mapping*, Vol. 45, No. e26595, pp. 1–14, 2024.

[8] Rodrigo Yáñez-Sepúlveda *et al.*, "Supervised Machine Learning Algorithms for the Classification of Obesity Levels Using Anthropometric Indices Derived from Bioelectrical Impedance Analysis", In *Scientific Reports*, Vol. 15, No. 30681, pp. 1–12, 2025.

[9] Xu, A.; Wang, T.; Yang, T.; Hu, K., "Extracting Multi-Dimensional Features for BMI Estimation Using a Multiplex Network", In *Symmetry*, Vol. 17, No. 6, pp. 1–16, 2025.

[10] V. Divya Raj; Shreya Motkar; N. Yamini Swamy; N. Sanjana; Shereen Sultana, "Prediction of BMI from Facial Image Using Deep Learning", In *International Research Journal of Engineering and Technology (IRJET)*, Vol. 10, No. 06, pp. 671–674, 2023.