IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

ML-Based Body Mass Index (BMI) Detection Using Facial Recognition

Manoj Dyavannavar, Ms. Sneha S, Pruthvi Raj C, Ravi Kumar N J, Sharanabasava,

Dept. Computer Science & Engineering (Data Science) PES Institute of Technology and Management

Shivamogga, Karnataka, India

Abstract: Estimating Body Mass Index (BMI) typically relies on physical measurements, such as height and weight, which can be challenging to obtain in remote or resource-limited environments. To tackle this issue, this study introduces an ML-based BMI prediction approach that relies solely on facial images. The system combines face detection, preprocessing, feature extraction, and several machine-learning models, including Random Forest, SVM, CNN, ResNet, MobileNet, and the Vision Transformer (DINOv2). By learning structural and visual patterns in facial features, the model can estimate BMI with high accuracy. This non-invasive solution is well-suited for telemedicine platforms, fitness monitoring tools, and large-scale public health applications.

Keywords: BMI Estimation, Machine Learning, Facial Recognition, CNN, ResNet, MobileNet, Vision Transformer.

I. INTRODUCTION

Body Mass Index (BMI) is a widely used indicator for understanding a person's body fat levels by comparing their height and weight. It plays a key role in identifying health risks such as obesity, heart disease, and diabetes. However, traditional BMI measurement depends on physical tools and direct measurements, which are not always practical, especially in remote locations, large-scale surveys, or situations where medical equipment is unavailable. With the rapid development of Artificial Intelligence (AI) and Machine Learning (ML), new possibilities have emerged for estimating BMI without requiring physical measurements. This project explores an innovative method that predicts an individual's BMI using facial recognition technology. Studies have shown that facial features like face shape, cheekbone structure, jawline definition, and overall fat distribution often reflect a person's BMI.Building on these insights, the system analyzes facial features and predicts BMI levels accurately, offering a convenient and non-invasive alternative to traditional methods. This approach is beneficial in modern healthcare scenarios such as telemedicine, fitness tracking applications, and digital health platforms, where direct access to a person's height and weight may not be possible. The project looks at different machine-learning techniques. It includes traditional models like Support Vector Machines (SVM) and Random Forest. It also examines newer deep-learning architectures such as Convolutional Neural Networks (CNN), ResNet, and MobileNet. These models are compared to identify the best-performing method for BMI prediction. In today's data-driven world, AI and computer vision technologies offer faster, contactless, and more scalable solutions for health analysis. By using CNN-based feature extraction to capture subtle facial details such as skin texture, contours, and structural patterns, the system can estimate BMI reliably without relying on manual measurements. The models are trained on a dataset of facial images matched with known BMI values. This allows for precise predictions for new individuals. Overall, this AI-powered framework provides a convenient, automated, and privacy-friendly way to estimate BMI. It supports personalized health monitoring, early detection of obesity or undernutrition, and enhances modern medical applications with efficient and accessible health assessment tools.

II. LITERATURE SURVEY

Recent developments in artificial intelligence and computer vision have greatly impacted BMI estimation through facial analysis. Earlier studies primarily relied on manual anthropometric measurements; however, contemporary works integrate deep learning, geometric modeling, and transformer-based architectures to improve prediction accuracy and robustness. In [1], Siddiqui et al. introduced one of the first deep learning frameworks for estimating BMI from facial images. Their pipeline involved face detection, illumination correction, and feature extraction using CNN-based regression models. The study demonstrated that mid-level convolutional features capture discriminative adiposity-related facial cues such as cheek fullness and jawline structure, leading to improved BMI prediction performance. Despite promising results, the authors noted limitations associated with demographic imbalance, pose variations, and lighting inconsistencies. A region-centric approach was proposed in [2], where Yousaf et al. applied semantic segmentation to isolate key facial zones before prediction. By focusing on regions highly correlated with adiposity (e.g., cheeks, mandible), the model reduced interference from irrelevant pixels and enhanced robustness under varying environmental conditions. Although the segmentation-based method improved accuracy, but it required high-quality masks, making real-time execution more computationally demanding. To address challenges in whole-face processing, Aarotale et al. introduced Patch BMI-Net in [3]. It is an ensemble framework that examines multiple facial patches independently. Each lightweight CNN learns local adiposity features, and their aggregated predictions produce a stable BMI estimate. This localized learning strategy reduces sensitivity to lighting and pose variations, making it especially suitable for mobile health applications where computing resources are limited. Fairness concerns were examined by Siddiqui et al. in [4], who evaluated demographic bias in facial BMI prediction systems. Their findings showed that models trained on unbalanced datasets often gave different predictions based on ethnicity, age, and gender groups. The study emphasized the need for fairness-aware methodologies, including balanced sampling, adversarial debiasing, and transparent model interpretation to ensure equitable healthcare outcomes. A complementary geometric approach was proposed in [5], where Pawade et al. utilized facial landmarks to compute explicit measurements—such as facial ratios, curvature features, and contour distances—for BMI regression. Using classical ML algorithms like SVM and Random Forest, the method offered interpretability and computational efficiency. However, its accuracy depended heavily on precise landmark detection, which may be affected by occlusion or poor lighting. Generalization challenges were further analyzed in [6], where researchers found that models sometimes learned unintended background cues or image artifacts instead of true facial features. Their work highlighted the importance of data augmentation, domain adaptation, and noise-robust preprocessing to improve real-world performance. Although originally designed for hyperspectral image analysis, the hybrid 2D–3D attention mechanism introduced by Guo et al. in [7] provided valuable insights for facial BMI prediction. Their architecture used collaborative convolution layers with attention modules to capture both spatial and structural dependencies. These concepts inspired modern BMI models that emphasize important facial regions through attention mechanisms for improved interpretability. Real-time applications of facial BMI estimation were explored by Gadekallu et al. in [8], who designed a lightweight ML model for malnutrition detection using basic facial geometry. The study demonstrated feasibility in low-resource environments but remained sensitive to illumination variations and camera quality. Transformers have also emerged as powerful tools in medical imaging. Shamshad et al. in [9] discussed the shift from CNN-based local feature extraction toward transformer-based global feature modeling. Their work justified the integration of Vision Transformers (ViT) into BMI prediction pipelines, highlighting their strengths in capturing long-range dependencies and reducing reliance on large supervised datasets. Similarly, Nerella et al. in [10] highlighted the importance of transformer architectures in healthcare applications. Their findings suggest that multimodal transformer systems—combining facial images with demographic or clinical metadata could significantly improve BMI estimation accuracy and robustness.

III. RESEARCH METHODOLOGY

Figure 1: The methodology refers to the systematic process for collecting facial images, preprocessing, and extracting features, followed by training and evaluating machine learning models for BMI prediction using techniques like CNN, Random Forest, and SVM. It encompasses the data pipeline, algorithm selection, and validation steps to ensure robust, non-invasive BMI estimation through facial analysis.
In this section implementation of the proposed BMI Detection Using Facial Recognition model, algorithm, along with data exploration, processing, and model generation has been discussed, as shown in Fig.1.

A. Image Acquisition:

The process begins by capturing or uploading a facial image using a webcam, smartphone, or file upload interface. This step ensures that the system receives a clear and usable image, forming the basis for all further processing.

B. Image Preprocessing:

Once the image is acquired, it undergoes preprocessing to improve its quality and prepare it for analysis. Enhancements such as resizing, brightness normalization, color correction, and noise removal are applied to ensure consistency across all inputs. These steps help improve the accuracy of the next stages.

C. Face Detection:

In this stage, the system identifies and extracts the face region from the input image using detection techniques like Haar Cascades, MTCNN, or YOLO. This process removes unnecessary background information and allows the system to focus only on the facial area needed for BMI prediction.

D. Model Optimization Check:

Before moving to BMI analysis, the system verifies whether the trained model is fully optimized.

- If no, further fine-tuning, hyperparameter adjustment, or retraining is required, and the process loops back for improvement.
- If yes, the model is ready for precise BMI prediction and the system then moves on to feature extraction.

Figure 1: System Architecture

E. Facial Feature Extraction:

After verification, the system extracts meaningful facial features that correlate with BMI. Deep learning architectures such as CNNs, ResNet, or MobileNet identify key facial characteristics like cheek structure, jawline shape, facial width, and fat distribution patterns. These features form the numerical input data for BMI prediction.

F. BMI Prediction:

The extracted feature vectors are processed by machine learning or deep learning models include Random Forest, SVM, CNN, ResNet, or MobileNet. These models analyze the learned facial patterns and estimate the user's BMI value based on previously trained data. The prediction is non-invasive and relies entirely on visual cues.

G. Result Comparison:

The predicted BMI is compared to internal testing data or actual values to assess system performance. Metrics like Mean Absolute Error (MAE) and R^2 score help find the reliability and accuracy of the predictions. This step makes sure the results are consistent and trustworthy.

H. Output Generation:

Finally, the system displays the estimated BMI along with a corresponding health category such as underweight, normal, overweight, or obese. The output is shown in a clear, easy-to-read format. This helps people understand their health status through facial analysis.

VI. RESULTS

The Results and Discussion chapter presents output screenshots, system interfaces, and analyzes model predictions, demonstrating the platform's effectiveness in estimating BMI from facial images.

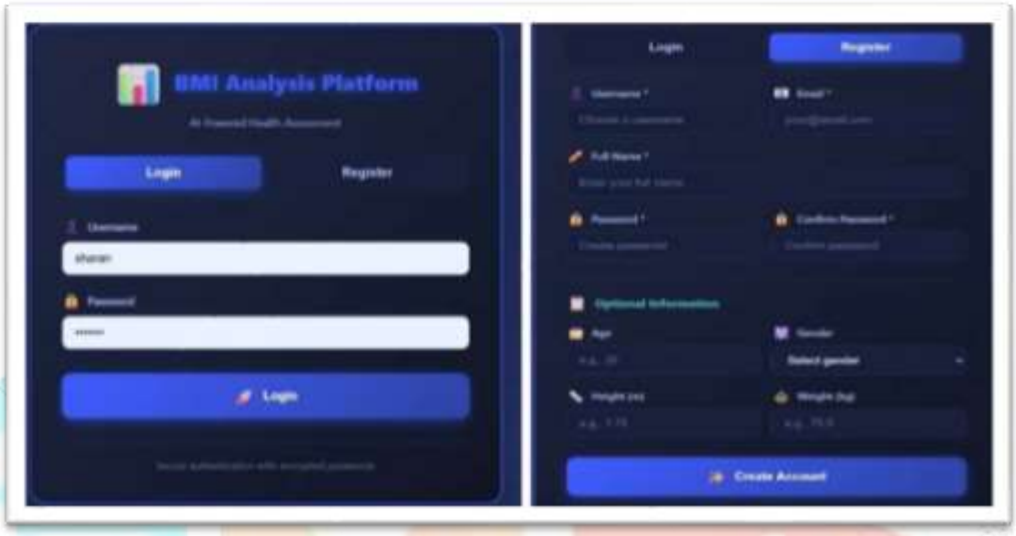

Figure 2: Login and Registration Interface

The above Figure 2 shows the Login and Registration interfaces of the BMI Analysis Platform, a health assessment system that uses AI for user authentication and data input. The Login Page (left panel) lets registered users securely access their accounts with a username and password. It features a clean, intuitive layout with encrypted authentication, ensuring data security and privacy.

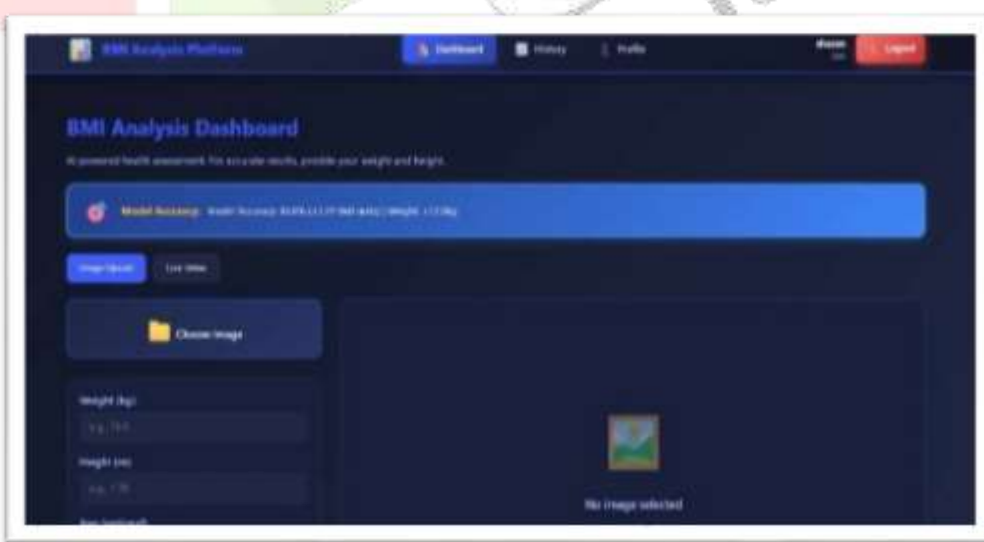

Figure 3: BMI Analysis Dashboard Interfaces

The above Figure 3 displays the BMI Analysis Dashboard of the AI-Powered Health Assessment Platform. This dashboard serves as the central workspace for users to upload images, input health parameters, and view predicted results. The interface is designed to be simple, responsive, and interactive. It has clear navigation tabs like Dashboard, History, and Profile. There is also a visible Logout button to ensure session security.

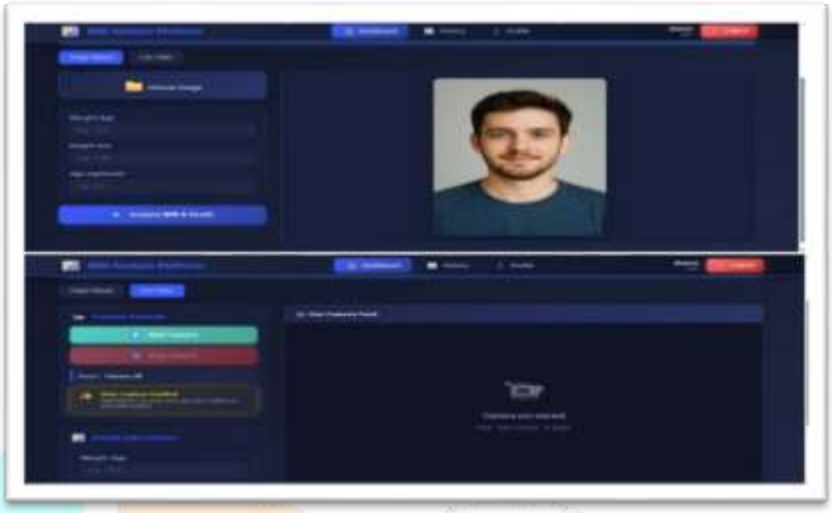

Figure 4: Image upload and live video capture interfaces

The above figures 4 illustrate two main features of the BMI Analysis Platform: the Image Upload Module and the Live Video Capture Module. Both parts are built to gather high-quality visual data that feeds into the system's AI-based BMI estimation model.

- **Image Upload Interface**: The Image Upload Interface allows users to either browse and select an existing image from their device or capture a new one using the connected camera. Once an image is uploaded, it is immediately previewed in the display area, enabling the user to verify clarity and facial positioning before analysis.
- **Live Video Capture Interface**: The Live Video Capture Interface enables real-time facial image acquisition through a webcam or camera device. Users can start or stop the camera using straightforward control buttons, while the Auto-Capture Enabled feature automatically detects a clear face frame and captures it for analysis.

Figure 5: User Registration Interface

Figure 5 above displays the User Registration Interface of the BMI Analysis Platform, which helps new users create an account in the system securely. This interface makes sure all essential information is gathered in a clear, user-friendly way to support personalized health analysis and secure access. The registration form includes important fields like Username, Email, Full Name, Password, and Confirm Password; all of these are marked as required.

VII. Conclusion

The proposed system effectively estimates Body Mass Index (BMI) from facial images using machine learning and facial recognition techniques. We explored several machine learning models, including Random Forest, Support Vector Machines, Convolutional Neural Networks, ResNet, and MobileNet, to see how well they predict BMI from facial features. The experimental results confirm that non-invasive and contactless BMI estimation is both feasible and reliable. This approach provides a fast, user-friendly, and accessible alternative to conventional BMI measurement methods, which typically require physical contact or specialized equipment. By enabling remote and continuous health monitoring, the system supports early identification of conditions such as obesity, malnutrition, and related health risks. Moreover, the work adds to the increasing use of artificial intelligence in healthcare. It offers a solution that can improve personalized health assessment and telehealth services.

REFERENCES

[1] H. Siddiqui *et al.*, "AI-driven BMI prediction using facial imagery," in *Proc. 19th IEEE Int. Conf. Mach. Learn. Appl. (ICMLA)*, 2020.

[2] N. Yousaf, S. Hussein, and W. Sultani, "BMI estimation from facial images using region-focused pooling with semantic segmentation," *Comput. Biol. Med.*, vol. 133, 2021.

[3] P. N. Aarotale, T. Hill, and A. Rattani, "Patch BMI-Net: A facial patch–based ensemble framework for BMI estimation," in *Proc. IEEE Int. Conf. Bioinf. Biomed. (BIBM)*, 2023.

[4] H. Siddiqui *et al.*, "A study on demographic bias in facial BMI prediction models," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR)*, 2022.

[5] D. Pawade *et al.*, "Facial-feature–based approach for BMI estimation," in *Proc. Int. Conf. Comput. Intell. Data Eng.*, Singapore: Springer, 2022.

[6] D. Pawade *et al.*, "Bias assessment in facial-analysis BMI prediction models," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR)*, 2022.

[7] H. Guo *et al.*, "Collaborative 2D–3D attention network for hyperspectral image classification," *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.*, vol. 13, 2020.

[8] T. R. Gadekallu *et al.*, "Real-time facial-image-based BMI prediction and malnutrition detection using ML techniques," *IET Image Process.*, vol. 16, pp. 647–658, 2021.

[9] F. Shamshad *et al.*, "A review on the use of transformers in medical imaging," *Med. Image Anal.*, 2023.

[10] S. Nerella *et al.*, "A survey of transformer applications in healthcare," *arXiv preprint*, 2023.