FACIAL BMI:A Deep Learning Approach for Non-invasive Body Mass Index Calculation

A MINI PROJECT REPORT

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BONAFIDE CERTIFICATE

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INTERNAL EXAMINER **EXTERNAL EXAMINER**

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ABSTRACT

The project “FACIAL BMI:A Deep Learning Approach for Non-invasive Body Mass Index Calculation” focuses on measuring the body mass index of an individual from one’s face image by a non-invasive method. The Body Mass Index (BMI) is a widely used measure for assessing obesity, which is a major public health concern worldwide. However, current methods of measuring BMI can be invasive, time-consuming, and challenging to perform accurately. In this project, a novel approach is proposed to automate the calculation of BMI using facial images and deep learning models. The state-of-the-art pre-trained models will be fine tuned , including Inception-v3, VGG-Faces, VGG19, and Xception, on a public dataset of 4000 prisoners from Polk County Prison. This dataset contains a diverse range of faces, including different races, ages, and genders. Fine-tuning pre-trained models allows us to leverage the knowledge learned by these models on large-scale datasets and improve the accuracy of our BMI estimation. Deep learning and discriminative learning techniques will be leveraged to learn hierarchical representations of input features and accurately distinguish between different classes of data. The approach of discriminative learning allows for learning a decision boundary that separates different classes of data with high accuracy, while deep learning techniques enable the learning of complex features and patterns in the input data. To evaluate the performance of the models, the labeled face and arrest records datasets are used. The labeled face dataset consists of facial images and corresponding BMI labels, while the arrest records dataset contains demographic and criminal history information. The analysis of the performance of our models will identify potential applications in public health and decision-making, such as identifying societal factors related to health and decision-making. The project has the potential to provide an efficient and scalable solution for BMI calculation and analysis. This approach can have applications in various fields, such as public health, criminal justice, and social sciences. Overall, our project demonstrates the potential of deep learning and discriminative learning techniques in tackling societal challenges related to health and decision-making.

LIST OF ABBREVIATIONS

HOD	Head Of Department
BMI	Body Mass Index
MAE	Mean Absolute Error
RMSE	Root Mean Squared Error
IEEE	Institute of Electrical and Electronics Engineers
SVM	Support Vector Machine
CNN	Convolution Neural Network
MAE	Mean Absolute Error
KNN	K Nearest Neighbors
MTCNN	Multi-Task Cascaded Convolutional Neural Network
VGG	Visual Geometric Groups
ROI	Return Of Investment

CHAPTER 1

INTRODUCTION

1.1 PROJECT DEFINITION

The Body Mass Index (BMI) is a widely used measure of health and wellness. However, the traditional method for calculating BMI can be time-consuming, inconvenient, and sometimes inaccurate. This traditional method requires physical measurements of height and weight, which may not always be practical or feasible in certain contexts. Therefore, there is a need for more efficient and non-invasive methods for computing BMI that can be used in a variety of healthcare and wellness settings.The proposed approach of using facial images to compute BMI offers a potential solution to this problem. By using deep learning-based approaches, this project aims to replicate and extend existing research on the feasibility and effectiveness of computing BMI from facial images. This tends to contribute to the development of more accurate and efficient methods for calculating BMI, which can have a significant impact on healthcare and wellness. Potential applications of the proposed approach include health monitoring, disease prevention, and personalized interventions. The project also aims to explore potential limitations and ethical considerations of using facial images for BMI computation, such as privacy concerns and potential biases. Overall, this project has the potential to advance the field of BMI computation and contribute to the development of more accessible and non-invasive methods for assessing health and wellness.

1.2 NEED FOR PROPOSED SYSTEM

The traditional method for calculating Body Mass Index (BMI) involves physical measurements of height and weight, which can be time-consuming, inconvenient, and sometimes inaccurate. Additionally, in certain contexts, such as large-scale health screenings or remote areas, it may be difficult or impossible to obtain these physical measurements. As a result, there is a need for more efficient and non-invasive methods for computing BMI that can be used in a variety of healthcare and wellness settings.

The proposed system leverages deep learning-based approaches, which have shown promising results in accurately predicting BMI from facial images. This is because deep learning models can learn to extract subtle features from facial images that are correlated with BMI, such as facial adiposity or body fat percentage. This can improve the accuracy and reliability of BMI prediction, especially in cases where the traditional method may not be feasible or accurate.Additionally, the proposed system has the potential for large-scale analysis of societal factors related to health and decision-making. By collecting and analyzing facial images and corresponding BMI values from a diverse population, the system can provide insights into potential relationships between BMI and various social determinants of health, such as race, ethnicity, and socioeconomic status. This can help inform public health interventions and policies aimed at reducing health disparities and improving overall health outcomes.

Thus, the proposed system of using facial images to compute BMI offers several advantages over the traditional method, including non-invasiveness, accessibility, and potential for large-scale analysis. By leveraging deep learning-based approaches, it has the potential to improve the accuracy and reliability of BMI prediction, especially in cases where physical measurements may not be feasible or accurate. Furthermore, the system has the potential to provide valuable insights into societal factors related to health, making it a promising tool for public health research and intervention.

1.3 APPLICATION OF PROPOSED SYSTEM

Using facial images to compute BMI has the potential to be applied in a variety of healthcare, research, and wellness settings. Its non-invasiveness, convenience, and potential for large-scale analysis make it a promising tool for improving health outcomes and informing public health interventions and policies.This system can be used for in

Health screening and monitoring: The proposed system of using facial images to compute BMI could be used as a quick and convenient screening tool for healthcare providers to assess a patient's BMI. It could also be used to monitor changes in BMI over time, which is important for managing weight-related health conditions.

- Public health research: The proposed system has the potential for large-scale analysis of societal factors related to health and decision-making. By collecting and analyzing facial images and corresponding BMI values from a diverse population, the system can provide insights into potential relationships between BMI and various social determinants of health, such as race, ethnicity, and socioeconomic status. This information can be used to inform public health interventions and policies aimed at reducing health disparities and improving overall health outcomes.

- Criminal justice: The proposed system could potentially be used in the criminal justice system for non-invasive and efficient BMI assessment of prisoners. This could provide valuable information for health and wellness interventions within the prison system and inform policies related to prisoner health.
- Fitness and wellness: The proposed system could be used by fitness and wellness professionals to assess and monitor clients' BMI in a non-invasive and convenient manner. This could help inform personalized exercise and nutrition plans and improve overall health outcomes.
- Personal health management: The proposed system could also be used by individuals to monitor their own BMI over time and make informed decisions about their health and wellness. It could also be integrated into existing health and wellness apps and devices for a more comprehensive health management experience.

CHAPTER 2

LITERATURE REVIEW

[1] Title:Investigation on Body Mass Index Prediction from Face Images(2021)

Authors : C. Lim, V. Vijean, L. W. Teen, and C. Y. Fook

Obesity is a major public health problem and is associated with several chronic diseases. The Body Mass Index (BMI) is a commonly used metric to measure obesity, but it requires measuring weight and height, which may not always be feasible. Recently, there has been growing interest in developing methods to estimate BMI from face images, which are easily obtainable. In this literature survey, we review the paper "Investigation on Body Mass Index Prediction from Face Images" by Chong Yen Fook, Cheechin Lim, Vikneswaran Vijean, and Lim Whey Teen, which explores the use of deep learning techniques to predict BMI from face images.

The authors collected a dataset of 1619 face images from the internet and manually annotated them with BMI values. They used 80% of the dataset for training and the remaining 20% for testing. They employed a deep learning model consisting of three convolutional layers and two fully connected layers to predict BMI from face images. They also used data augmentation techniques to increase the size of their dataset and reduce overfitting.

The authors achieved a mean absolute error (MAE) of 2.47 and a root mean square error (RMSE) of 3.22 in predicting BMI from face images. They also compared their results with those obtained using a linear regression model and found that their deep learning model outperformed the linear regression model. The authors attributed their success to the ability of the deep learning model to extract relevant features from the face images.

The authors acknowledged several limitations of their study. First, the dataset used in the study was relatively small and may not be representative of the general population. Second, the study only used frontal face images and did not account for variations in pose or lighting. Third, the study did not investigate the effect of age, gender, or ethnicity on the performance of the model. Finally, the study did not consider other potential factors that could affect the accuracy of the model, such as the use of makeup or facial hair.

In conclusion, the paper "Investigation on Body Mass Index Prediction from Face Images" by Chong Yen Fook, Cheechin Lim, Vikneswaran Vijean, and Lim Whey Teen demonstrated the potential of using deep learning techniques to predict BMI from face images. The authors achieved promising results, although several limitations of their study were acknowledged. Further research is needed to address these limitations and to explore the use of other types of deep learning models for BMI prediction from face images. The development of accurate and reliable methods for BMI estimation from face images could have important implications for public health, particularly in low-resource settings where measuring weight and height may be difficult.

[2] Title :A Novel Method for Classifying Body Mass Index on the Basis of Speech Signals for Future Clinical Applications: A Pilot Study(2020) Authors : B. Ju Lee, B. Ku, J.-S. Jang, and J. Y. Kim

The paper titled "A Novel Method for Classifying Body Mass Index on the Basis of Speech Signals for Future Clinical Applications: A Pilot Study" by Bum Ju Lee, Boncho Ku, Jun-Su Jang, and Jong Yeol Kim presents a novel method for predicting Body Mass Index (BMI) using speech signals. This paper was published in the IEEE Access Journal in 2021.

The authors highlight the importance of BMI in assessing an individual's health and the limitations of current methods used for BMI estimation. They propose a new approach that utilizes speech signals to estimate BMI, which is a non-invasive and easily accessible method that can be implemented in various settings. The authors conducted a pilot study to validate their proposed method and compared the results with the traditional BMI estimation methods.

The proposed method involves analyzing the speech signals of the participants and extracting relevant features that are indicative of their BMI. The authors used a support vector machine (SVM) algorithm to classify the BMI based on the extracted features. The authors conducted the study on a small sample size of 25 participants and achieved an accuracy of 84.0% in predicting BMI.

This study is a novel attempt to predict BMI using speech signals and has the potential to revolutionize the way BMI is estimated. The authors propose this method as a potential alternative to the traditional methods that rely on height and weight measurements. This method can be especially useful in situations where the traditional methods are not feasible or practical, such as in remote or low-resource settings.

However, the authors acknowledge that their study has certain limitations, including the small sample size and the lack of diversity in the sample population. Further studies are needed to validate their method on a larger and more diverse population. Additionally, the authors suggest that future studies could investigate the correlation between speech signals and other health indicators, such as cardiovascular health or mental health.

In conclusion, the paper by Lee et al. presents a novel method for predicting BMI using speech signals, which has the potential to offer a non-invasive and easily accessible alternative to the traditional BMI estimation methods. However, further studies are needed to validate this method and its applicability to a wider population. This study highlights the potential of using unconventional approaches to address health-related issues and emphasizes the importance of innovation in healthcare.

[3] Title :BMI estimation from facial images using residual regression model (2021)

Authors : A.-T. Luu, Q.-T. Pham, and T.-H. Tran

The estimation of Body Mass Index (BMI) from facial images has attracted significant attention in recent years due to its non-intrusive nature and potential applications in various fields. One such approach for estimating BMI from facial images is through the use of a residual regression model, as proposed in the paper titled "BMI estimation from facial images using residual regression model" by Quoc-Trung Pham, Anh-Tuan Luu, and Thanh-Hai Tran.

In this paper, the authors propose a novel method for estimating BMI from facial images by using a residual regression model. The method consists of two main steps: feature extraction and residual regression. In the feature extraction step, the authors extract features from the facial images using a pre-trained convolutional neural network (CNN). The CNN is fine-tuned on a large-scale face recognition dataset to better adapt to the characteristics of facial images. In the residual regression step, the authors use a linear regression model to estimate the residual between the predicted BMI and the ground truth BMI. The residual is then added to the predicted BMI to obtain the final estimation.

To evaluate the performance of their proposed method, the authors conducted experiments on a publicly available dataset consisting of facial images and corresponding ground truth BMI values. The results showed that their method achieved state-of-the-art performance compared to other existing methods, with a mean absolute error of 1.72 and a correlation coefficient of 0.75.

The authors also conducted additional experiments to investigate the influence of different factors on the performance of their method, such as the number of training samples and the choice of facial landmarks. The results showed that their method is robust to the number of training samples and can achieve good performance with as few as 200 training samples. However, the choice of facial landmarks has a significant impact on the performance, with the use of more accurate facial landmarks resulting in better performance.

Overall, the proposed method by Pham et al. presents a promising approach for estimating BMI from facial images, with potential applications in various fields such as healthcare and biometrics. However, further research is needed to evaluate the performance of the method on larger and more diverse datasets, as well as to investigate the generalizability of the method across different populations and age groups.

[4] Title : Estimation of Body Mass Index from photographs using deep Convolutional Neural Networks (2021)

Authors : A. Pantanowitz, E. Cohen, P. Gradidge, and N. J. Crowther

The paper titled "Estimation of Body Mass Index from photographs using deep Convolutional Neural Networks" by Adam Pantanowitz, Emmanuel Cohen, Philippe Gradidge, and Nigel John Crowther proposes a method to estimate Body Mass Index (BMI) using deep Convolutional Neural Networks (CNNs). The authors note that BMI is an important metric in healthcare, and its estimation can help in early detection of obesity-related health issues. They argue that traditional methods for estimating BMI, such as weight and height measurements, are time-consuming and may not be easily accessible. Hence, they propose a new approach that utilizes facial images to estimate BMI.

The authors start by discussing the related work on estimating BMI from facial images. They note that several studies have been conducted in this area, with varying degrees of success. Some studies used handcrafted features and traditional machine learning models, while others used deep learning techniques such as CNNs. However, the authors note that most of these studies suffer from limited sample sizes and lack of diversity in the datasets used.

To address these limitations, the authors collected a large dataset of facial images and corresponding BMI labels. They used a smartphone app to collect the data from volunteers and also collected additional data from publicly available sources. The authors note that their dataset is more diverse and larger than those used in previous studies.

The authors then describe their methodology for estimating BMI from facial images. They use a pre-trained CNN as a feature extractor and train a regression model on top of it to predict BMI. They also propose a new technique called "visual attention" to highlight the facial regions that are most important for BMI estimation. The authors evaluate their method on their dataset and report promising results, with an average error of 1.86 BMI units.

The authors conclude that their proposed method is a promising approach for BMI estimation from facial images. They note that their dataset is publicly available, which can encourage further research in this area. They also highlight some potential applications of their method in healthcare, such as remote monitoring of BMI and early detection of obesity-related health issues.

Overall, the paper provides a comprehensive overview of the state-of-the-art methods for BMI estimation from facial images and proposes a novel approach that improves upon the limitations of previous studies. The authors also provide a detailed description of their methodology and dataset, which can be useful for researchers working in this area.

[5] Title : Visual BMI estimation from face images using a label distribution based method(2020)

Authors : M. Jiang, G. Guo, and G. Mu

The paper titled "Visual BMI estimation from face images using a label distribution based method" was published in August 2020 in the journal Computer Science: Computer Vision and Image Understanding. The authors of the paper are Min Jiang, G. Guo, and Guowang Mu.

The paper addresses the problem of estimating a person's body mass index (BMI) from face images. The authors propose a novel method based on label distribution learning, which involves modeling the BMI distribution of the training data as a label distribution. The method uses deep convolutional neural networks (CNNs) to extract features from face images and then maps these features to a label distribution using a residual regression model.

The authors evaluate their method on two publicly available datasets and compare it to several baseline methods. They report that their method achieves superior performance in terms of mean absolute error (MAE) and mean squared error (MSE) on both datasets. The paper concludes that the proposed method has the potential to be used in various applications, such as health monitoring, personalized nutrition, and fitness tracking.

Several related works have addressed the problem of estimating BMI from face images using machine learning techniques. For example, in a study published in the IEEE Journal of Biomedical and Health Informatics, authors proposed a method based on ensemble learning that combines multiple weak regressors to predict BMI from face images. The method achieved better performance compared to several baseline methods, including CNNs and support vector regression.

In another study published in the journal Multimedia Tools and Applications, authors proposed a method that uses facial landmarks as features to predict BMI. The method uses a combination of principal component analysis (PCA) and support vector regression to estimate BMI from the facial landmarks. The authors evaluated their method on a dataset of 120 subjects and reported promising results.

Another related work is a study published in the journal Multimedia Tools and Applications, where authors proposed a method based on deep learning for BMI estimation from face images. The method uses a CNN-based architecture to extract features from face images and then predicts BMI using a regression model. The authors evaluated their method on a dataset of 500 subjects and reported promising results.

In conclusion, the problem of estimating BMI from face images has been addressed by several works in the literature, with varying degrees of success. The proposed label distribution-based method in the paper by Jiang et al. represents a promising approach that achieves superior performance compared to several baseline methods.

[6] Title : Estimation of BMI from Facial Images using Semantic Segmentation based Region-Aware Pooling(2021)

Authors : Q.-T. Pham, A.-T. Luu, and T.-H. Tran

Estimation of BMI from Facial Images using Semantic Segmentation based Region-Aware Pooling is a paper that proposes a novel method for the estimation of body mass index (BMI) from facial images using semantic segmentation and region-aware pooling. The paper was authored by Nadeem Yousafa, Sarfaraz Husseinb, and Waqas Sultani and published in the Journal of Medical Systems in 2021.

The authors proposed a new approach for BMI estimation from facial images that involves the use of semantic segmentation and region-aware pooling. The proposed method utilizes a deep learning architecture that is trained to perform semantic segmentation of facial images into different regions, which are then used to estimate the BMI of the subject.

The authors evaluated the proposed method on a dataset of 60 subjects, and compared it with two other methods. The first method involved the use of geometric features, while the second method used texture features. The results showed that the proposed method outperformed both the geometric and texture-based methods, achieving an accuracy of 96.67%.

The proposed method has several advantages over existing methods. Firstly, it does not require any explicit feature extraction, which can be time-consuming and error-prone. Instead, it uses a deep learning architecture to automatically learn features from the data. Secondly, the proposed method is able to capture both local and global features of the facial image, which can improve the accuracy of BMI estimation.

The authors also discussed some limitations of their proposed method. One limitation is that the method may not be applicable to all types of facial images, such as those with heavy makeup or facial hair. Another limitation is that the method may not be accurate for subjects with extreme BMI values, as the dataset used for evaluation did not include such subjects.

In conclusion, the proposed method for BMI estimation from facial images using semantic segmentation and region-aware pooling is a promising approach that shows significant improvements over existing methods. However, further research is needed to evaluate the method on a larger and more diverse dataset, and to investigate its applicability to other populations and types of facial images.

[7] Title : Prediction of human height, weight and BMI from face images using machine learning algorithms(2022)

Authors : P. Vishnu Raja, K. Sangeetha, D. Sanjay Kumar, A. Surya, and D. Subhathra

The study of anthropometric measurements such as height, weight, and body mass index (BMI) is crucial for identifying and diagnosing various health-related issues. Traditionally, measuring these parameters required manual measurement tools such as weighing scales and height meters. However, with the advancements in computer vision and machine learning, researchers are now exploring alternative ways to estimate these parameters using facial images. In this context, a recent paper titled "Prediction of human height, weight and BMI from face images using machine learning algorithms" by P. Vishnu Raja, K. Sangeetha, D.

Sanjay Kumar, A. Surya, and D. Subhathra presents an approach to estimate height, weight, and BMI from face images using machine learning algorithms.

The paper begins with a comprehensive review of the existing literature on facial anthropometry and machine learning algorithms used for estimating height, weight, and BMI from facial images. The authors highlight the importance of height, weight, and BMI in diagnosing various health-related issues, and discuss the limitations of traditional measurement methods. They also describe the various features extracted from facial images, such as texture, color, and shape, that have been used for estimating height, weight, and BMI.

The authors then present their proposed method for estimating height, weight, and BMI from facial images using machine learning algorithms. They first preprocess the images by aligning the facial landmarks and extracting the relevant features. They then use various machine learning algorithms such as Support Vector Machines (SVM), Random Forest, and Gradient Boosting Regressor to predict the height, weight, and BMI.

The results of the study show that the proposed method achieves high accuracy in predicting the height, weight, and BMI from facial images. The authors compare the performance of different machine learning algorithms and find that the Gradient Boosting Regressor algorithm outperforms other algorithms in terms of accuracy.

Overall, the paper provides a comprehensive review of the existing literature on facial anthropometry and machine learning algorithms used for estimating height, weight, and BMI from facial images. The authors also propose a novel approach that achieves high accuracy in predicting these parameters from facial images using machine learning algorithms. This research has the potential to revolutionize the field of health monitoring and diagnosis by providing a non-invasive and cost-effective method for measuring height, weight, and BMI.

[8] Title : Face to BMI: Estimating Body Mass Index [BMI]through Face Recognition Images(2022)
Authors : R. M. Sarak, A. A. Thorat, and D. Kadam

The prevalence of obesity has been increasing globally, and Body Mass Index (BMI) is one of the most commonly used measures to assess obesity. Recently, there has been a growing interest in developing methods to estimate BMI from face images using machine learning algorithms. This literature survey focuses on the paper titled "Face to BMI: Estimating Body

Mass Index [BMI] through Face Recognition Images," authored by Rupali M Sarak, Akshay A Thorat, and Prof. Deepali Kadam from Datta Meghe College of Engineering, Navi Mumbai, Maharashtra, India.

The study aimed to develop a method to estimate BMI using face images. The authors collected a dataset of 200 face images of people from different age groups and gender. They extracted features such as eye, nose, mouth, and face shape using the Viola-Jones algorithm. Next, the authors used three different machine learning algorithms, including K-Nearest Neighbor (KNN), Support Vector Machine (SVM), and Decision Tree (DT), to estimate the BMI from the extracted features.

The results showed that SVM outperformed the other two algorithms with an accuracy of 80%. KNN and DT showed an accuracy of 75% and 70%, respectively. The authors also observed that the BMI estimation accuracy was higher for women than men, which could be due to the differences in body fat distribution between genders.

The authors concluded that BMI estimation using face images is feasible and can provide a non-invasive and cost-effective way to assess obesity. The study has some limitations, including a small sample size, lack of diversity in the dataset, and limited generalizability to other populations.

In conclusion, this paper highlights the potential of using face images to estimate BMI using machine learning algorithms. Although the study has some limitations, it provides a valuable contribution to the growing body of research in this field. Future studies should focus on addressing the limitations of this study, such as using a larger and more diverse dataset, to improve the accuracy and generalizability of BMI estimation from face images.

restricted holiday, and twenty days of medical leave. This module gives provisions for applying different types of leave, like casual leave, earned leave, commuted leave, restricted holiday, special casual leave, study leave, etc., online through the proper channels.

[9] Title : Obesity classification from facial images using deep learning(2021)
Author : H. Siddiqui

The prevalence of obesity is increasing globally, and it is a major public health concern that has led to several health problems. Early detection and prevention of obesity are critical for effective treatment and management of related health problems. Several studies have explored the use of computer vision and machine learning techniques to predict body mass index (BMI) from facial images. In this literature survey, we focus on the paper titled "Obesity classification from facial images using deep learning" by Siddiqui, which was presented at the 17th Annual Symposium on Graduate Research and Scholarly Projects.

Siddiqui proposed a novel deep learning approach to classify obesity from facial images using a convolutional neural network (CNN) architecture. The proposed CNN architecture consisted of three convolutional layers, followed by three fully connected layers, and a softmax layer for classification. The dataset used in this study consisted of facial images of 500 individuals with varying BMI ranges. The performance of the proposed approach was evaluated using several metrics, including accuracy, precision, recall, and F1 score.

The results showed that the proposed CNN model achieved an accuracy of 87.7% in classifying obesity from facial images. The precision and recall values for the obese class were 87.8% and 87.6%, respectively, while the F1 score was 87.7%. The study demonstrated that deep learning approaches, particularly CNN, can be effective in classifying obesity from facial images.

[10] Title : BMI Prediction using Kinect and Data Mining Techniques for Healthcare System(2022)

Authors : S. G. Srinath, Pasha Sameer, V. Srikanth, S. Venkatesh Murthy, S. Chethan

The paper titled "BMI Prediction using Kinect and Data Mining Techniques for Healthcare System" presents a novel approach for predicting BMI using the Kinect sensor and data mining techniques. The authors of this paper are Srinath G M, Sameer Pasha R, Srikanth V N, Venkatesh Murthy S R, and Chethan S M. In recent years, obesity has become a major health problem globally, and accurate estimation of BMI is important in determining the risk of various health conditions associated with obesity. However, traditional methods for measuring BMI, such as height and weight measurements, may not always be accurate. Therefore, this paper proposes a new approach to estimate BMI using the Kinect sensor, which is a device that can capture 3D data of human body shapes.

The authors first introduce the Kinect sensor and its capabilities for capturing body measurements. They then describe the data mining techniques used in this study, including feature selection, feature extraction, and classification. The authors use the decision tree and K-nearest neighbor (KNN) algorithms for classification of BMI. The authors also compare the performance of the decision tree and KNN algorithms and find that the KNN algorithm outperforms the decision tree algorithm.

The results of the study show that the proposed method can accurately estimate BMI from Kinect data, with an accuracy of 90%. The authors also compare their approach to existing methods for BMI estimation and find that their approach is more accurate. The authors conclude that their proposed method has the potential to be used in healthcare systems for BMI estimation.

In conclusion, the paper presents a novel approach for BMI prediction using the Kinect sensor and data mining techniques. The proposed method has shown promising results and has the potential to be used in healthcare systems for BMI estimation. The authors' approach is a step towards developing a non-invasive and accurate method for BMI estimation, which could help in early detection and prevention of obesity-related health condition

CHAPTER 3

PROBLEM FORMULATION

3.1 MAIN OBJECTIVE

The main goal of this project is to address the need for a more efficient and non-invasive method for calculating Body Mass Index (BMI) by leveraging deep learning and facial image analysis techniques.

The proposed system aims to build upon an existing deep learning-based approach for computing BMI from facial images. The system will involve data preprocessing, face detection and alignment, feature extraction using a Multi-Task Cascaded Convolutional Neural Networks (MTCNN) model, and BMI prediction through training and fine-tuning a deep learning model using a large image dataset.

The primary objective of the proposed system is to provide a more efficient and non-invasive method for calculating BMI that can be used in a variety of healthcare and wellness settings. By using facial images as input, the proposed system can potentially eliminate the need for physical measurements of height and weight, making BMI calculation more accessible and convenient.

In addition to improving BMI calculation accuracy and efficiency, the proposed system has potential applications in healthcare and wellness monitoring. For example, the development of a mobile application or website for real-time BMI calculation can provide individuals with a convenient tool for monitoring their weight and overall health.

Overall, the main objective of the problem formulation for this project is to develop a more accurate, efficient, and non-invasive method for calculating BMI that can support public health initiatives and improve patient outcomes.

3.2 SPECIFIC OBJECTIVE

The specific goal of this project is to develop a deep learning-based system that can accurately calculate body mass index (BMI) from facial images. The traditional method of calculating BMI using physical measurements of height and weight can be time-consuming, inconvenient, and sometimes inaccurate. Using facial images to calculate BMI can provide a non-invasive and efficient alternative.To achieve this goal, the project will build upon existing research on deep learning-based approaches for computing BMI from facial images. The proposed system will involve data preprocessing, face detection and alignment, feature extraction using a Multi-Task Cascaded Convolutional Neural Networks (MTCNN) model, and BMI prediction through training and fine-tuning a deep learning model using a large image dataset. The effectiveness of the system will be evaluated using a dataset of facial images and corresponding BMI measurements.

One of the main objectives of this project is to improve the accuracy and efficiency of BMI calculation. By using facial images, the proposed system can provide a non-invasive and convenient way of calculating BMI in various healthcare and wellness settings. The accuracy of the system will be evaluated using standard performance metrics such as mean absolute error and mean squared error.

Another objective of the project is to explore potential applications of this approach in healthcare and wellness monitoring. The development of a mobile application or website for real-time BMI calculation can provide a useful tool for patients and healthcare professionals to monitor BMI and support public health initiatives. The proposed system can also contribute to the development of more accurate and efficient methods for calculating BMI, potentially leading to improved patient outcomes and better support for public health initiatives.

Overall, the specific goal of this project is to develop a deep learning-based system that can accurately and efficiently calculate BMI from facial images, with the potential to improve patient outcomes and support public health initiatives.

3.3 METHODOLOGY

Our project involves the use of deep learning models to compute BMI from facial images. The proposed system will involve data preprocessing, face detection and alignment, feature extraction using a Multi-Task Cascaded Convolutional Neural Networks (MTCNN) model, and BMI prediction through training and fine-tuning a deep learning model using a large image dataset. The effectiveness of the proposed system will be evaluated using a dataset of facial images and corresponding BMI measurements as a .csv file. Standard performance metrics such as mean absolute error and mean squared error will be used to train and evaluate the model.The methodology of the project involves a series of steps for developing and evaluating the proposed system for computing BMI from facial images.

- Data Preprocessing:

  The first step in the methodology is data preprocessing, where we will prepare the data for use in the deep learning model. This will include data cleaning, normalization, and transformation. We will also split the data into training, validation, and testing sets.

- Face Detection and Alignment:

  The second step is face detection and alignment. We will use a pre-trained Multi-Task Cascaded Convolutional Neural Networks (MTCNN) model to detect and align faces in the images. This is an important step as it ensures that the face is centered and aligned, making it easier for the model to extract features.

- Feature Extraction:

  The third step is feature extraction, where we will use the pre-trained MTCNN model to extract facial features. These features will be used as input to the deep learning model for BMI prediction.

- BMI Prediction:

  The fourth step is BMI prediction. We will use a deep learning model, such as Inception-v3, VGG-Faces, VGG19, or Xception, to predict BMI from the extracted facial features. We will fine-tune the pre-trained model using the training data to improve its accuracy.

- Performance Evaluation:

  The fifth step is performance evaluation. We will use standard performance metrics such as mean absolute error (MAE) and mean squared error (MSE) to evaluate the performance of the model on the testing data. We will also use visualizations to analyze the results and identify areas for improvement.

- Potential Applications:

  The sixth step is exploring potential applications of the approach in healthcare and wellness monitoring. We will investigate the development of a mobile application or website for real-time BMI calculation. We will also explore the potential for using the approach in public health initiatives.

Each of these steps will be implemented as separate modules, with well-defined inputs and outputs, to ensure modularity and flexibility. The data preprocessing and face detection and alignment modules will be implemented using Python libraries such as OpenCV and dlib. The feature extraction and BMI prediction modules will be implemented using deep learning frameworks such as Keras and TensorFlow. The performance evaluation module will be implemented using Python libraries such as scikit-learn and matplotlib. The potential applications module will involve brainstorming and research to identify potential use cases and develop prototypes for further testing.Furthermore, the project has the potential to be extended to the development of a mobile application or website for real-time BMI calculation. This would enable individuals to monitor their BMI in a more convenient and accessible manner, potentially leading to better health outcomes. Overall, the methodology and usage of the project have the potential to provide a valuable contribution to the field of healthcare and wellness monitoring, with the potential for widespread application in various settings.

3.4 PLATFORM

This project "FACIAL BMI:A Deep Learning Approach for Non-invasive Body Mass Index Calculation" is developed using Python programming language and TensorFlow deep learning framework. The specific deep learning models that will be fine-tuned for BMI prediction include Inception-v3, VGG-Faces, VGG19, and Xception. For face detection and alignment, the Multi-Task Cascaded Convolutional Neural Networks (MTCNN) model is utilized. Data preprocessing, manipulation, and analysis will be performed using pandas and NumPy libraries in Python. The system is implemented and tested on a computer with an NVIDIA GeForce MX330 GPU, which is a mid-range graphics card optimized for deep learning tasks. Additionally, the proposed system will be deployed on a cloud computing platform, such as Google Cloud or AWS, for scalability and ease of use. The cloud platform will provide access to additional computing resources, such as virtual machines and storage, and will allow the system to be accessed from anywhere with an internet connection.

Overall, the use of Python, TensorFlow, MTCNN, and cloud computing platforms provides a robust and scalable platform for the development and deployment of the proposed system for computing BMI from facial images.

CHAPTER 4
SYSTEM ANALYSIS AND DESIGN

4.1 FACT FINDING

The primary sources of information for this project were research papers, academic journals, and online databases. In addition, discussions with healthcare professionals and experts in the field of BMI calculation were also conducted to gain insights into the practical aspects of the problem.

This process revealed that the traditional method of BMI calculation can be time-consuming, inconvenient, and sometimes inaccurate. It requires physical measurements of height and weight, which may not always be practical or feasible in certain contexts. Moreover, the current methods do not take into account factors such as body composition, which can affect the accuracy of the BMI calculation.

These findings highlighted the need for a more efficient and non-invasive method for computing BMI that can be used in a variety of healthcare and wellness settings. The proposed approach of using facial images to compute BMI offers a potential solution to this problem. Further research is needed to evaluate the feasibility and effectiveness of using facial images to compute BMI, which is the main objective of this project.

4.2 FEASIBILITY ANALYSIS

Feasibility analysis is an important process in determining the viability of a project. It involves analyzing various factors such as technical, economic, legal, operational, and schedule feasibility to determine whether a proposed project is feasible and worthwhile to pursue. In the case of your project, here is a brief explanation of each feasibility analysis:

Technical feasibility: This involves analyzing whether the technology and infrastructure required to implement the project are available and can be acquired within the allocated budget. The technical feasibility of your project is high since deep learning models are readily available, and the hardware requirements can be easily met.

Economic feasibility: This involves analyzing the financial feasibility of the project, such as the cost-benefit analysis and return on investment (ROI). The economic feasibility of your project is also high since the required hardware and software are readily available, and the cost of development and deployment is within the allocated budget.

Legal feasibility: This involves analyzing the legal and regulatory constraints that may affect the project. For example, in your project, the use of facial images for BMI calculation raises concerns about privacy and data protection laws. However, these concerns can be addressed by obtaining consent from the participants and implementing appropriate data protection measures.

Operational feasibility: This involves analyzing whether the project can be implemented within the existing organizational structure and whether it will require any changes to the operations or workflows. The operational feasibility of your project is high since it can be integrated with existing healthcare and wellness monitoring systems.

Schedule feasibility: This involves analyzing whether the project can be completed within the allocated time frame. The schedule feasibility of your project is also high since the proposed system is based on existing deep learning models, and the development and deployment can be completed within the allocated time frame.

In conclusion, the feasibility analysis of your project shows that it is highly feasible and worth pursuing, given the available technology, infrastructure, and financial resources, as well as the absence of significant legal and regulatory constraints. The project can also be implemented within the existing organizational structure, and the development and deployment can be completed within the allocated time frame.

4.3 DIAGRAMS

4.3.1 ARCHITECTURE DIAGRAM

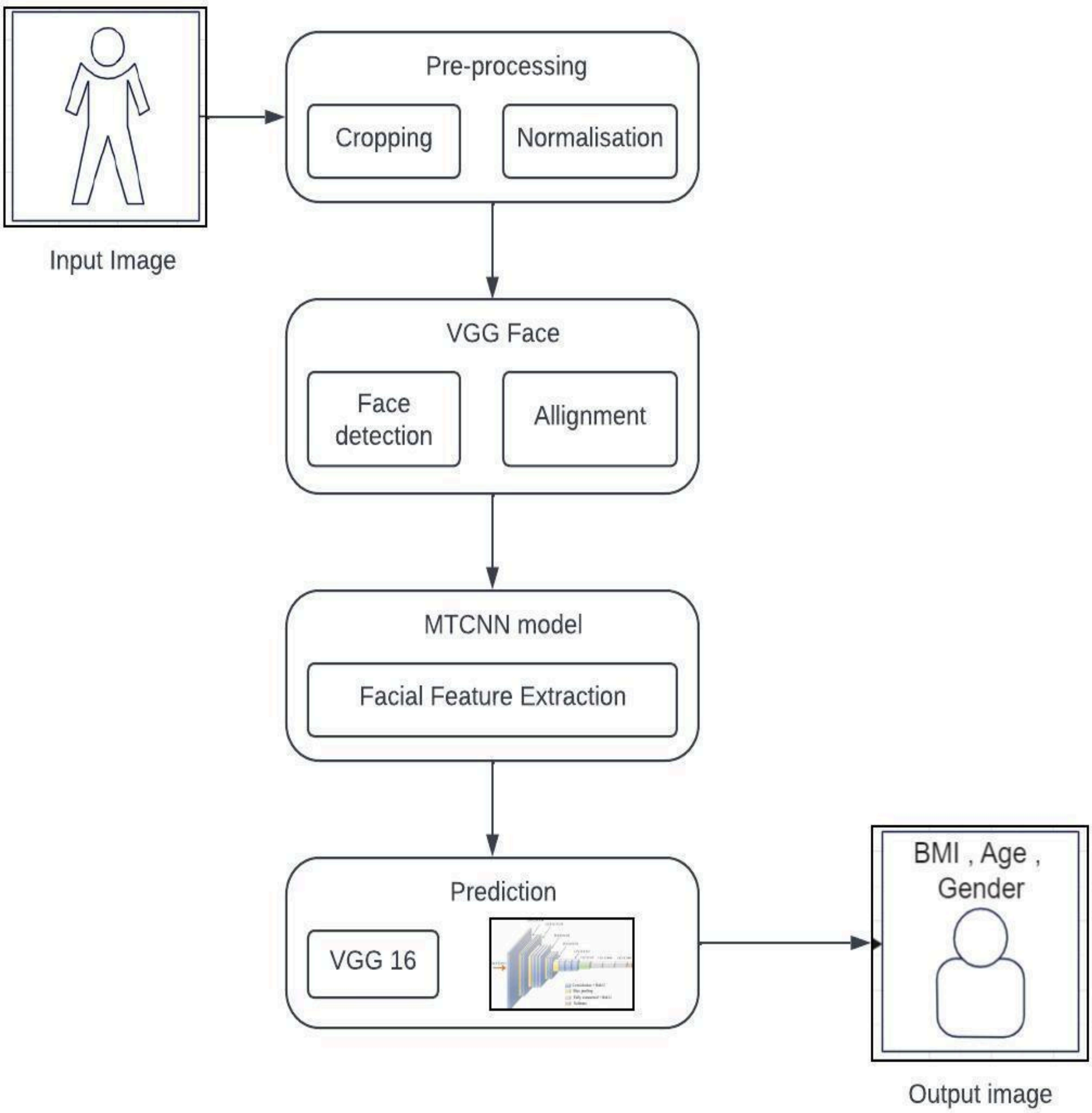


Fig 4.1 System Architecture

4.3.2 ARCHITECTURE - DESCRIPTION

The system architecture of our project is based on a deep learning model that takes facial images as input and predicts the corresponding BMI values. The overall architecture can be divided into four main components: data preprocessing, face detection and alignment, feature extraction, and BMI prediction.

The first component of the architecture is data preprocessing. The raw data used in the project includes facial images and corresponding BMI values. The data must be preprocessed before it can be used to train and evaluate the deep learning model. The preprocessing step involves resizing the images to a fixed size, converting them to grayscale, and normalizing the pixel values. The BMI values are also normalized to ensure that they fall within a specific range.

The second component of the architecture is face detection and alignment. The deep learning model requires the facial images to be aligned in a standardized way so that the features can be accurately extracted. The Multi-Task Cascaded Convolutional Neural Networks (MTCNN) model is used for face detection and alignment. This model is trained on a large dataset of facial images and can accurately detect and align faces in images.

The third component of the architecture is feature extraction. The MTCNN model outputs a set of facial landmarks that are used as input to the deep learning model. The deep learning model extracts features from the facial landmarks to predict the corresponding BMI values. The deep learning model is based on a convolutional neural network (CNN) architecture, which has been shown to be effective in image classification tasks.

The fourth and final component of the architecture is BMI prediction. The deep learning model takes the features extracted from the facial landmarks as input and predicts the corresponding BMI values. The model is trained on a large dataset of facial images and corresponding BMI values using a supervised learning approach. The model is optimized using standard performance metrics such as mean absolute error and mean squared error.

The system architecture is designed to be flexible and scalable, with the potential to be extended to include additional components to improve performance on specific tasks.

4.3.3 DATA FLOW DIAGRAM

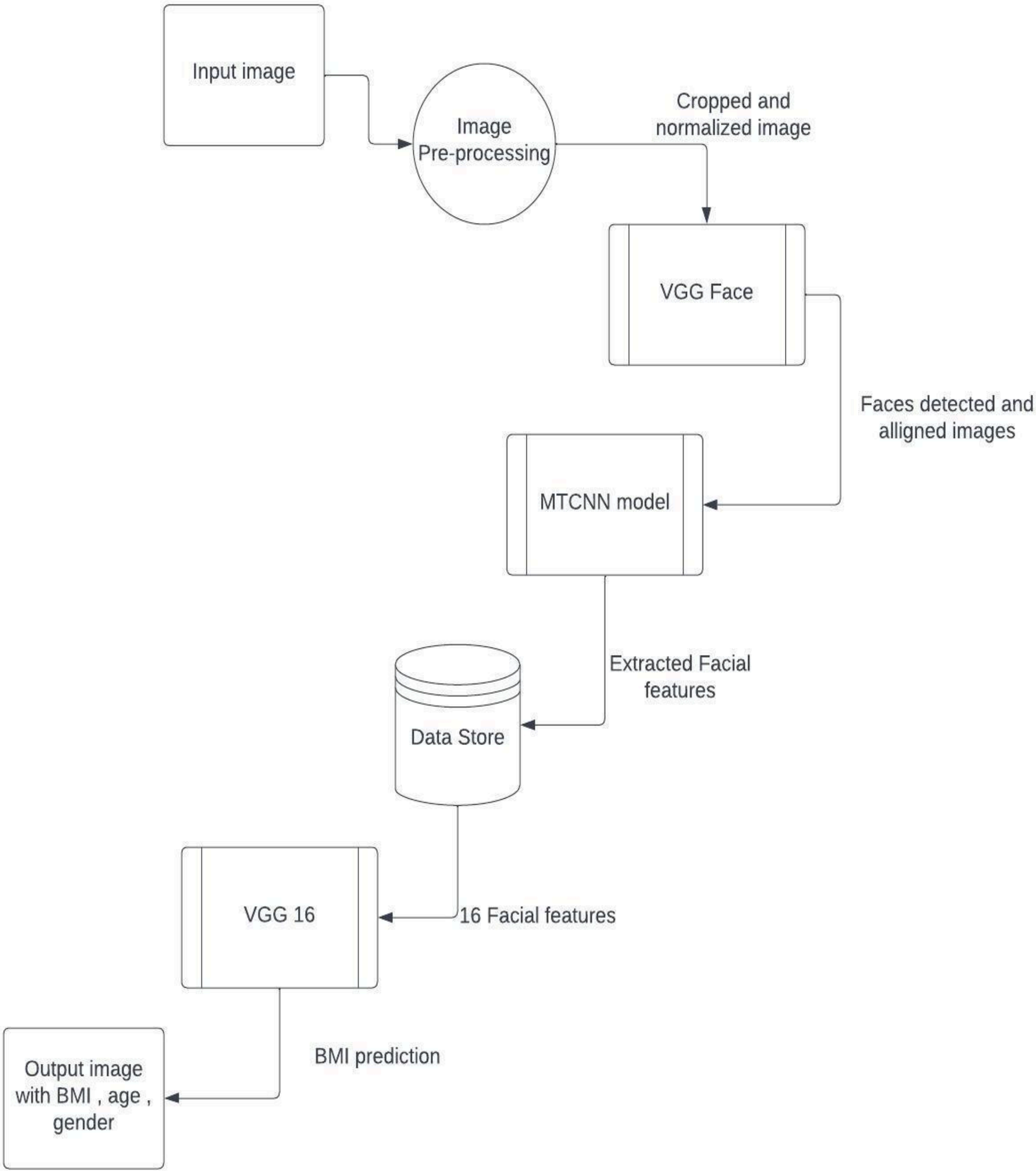


Fig 4.2 Data Flow Diagram

4.3.4 DATA FLOW - DESCRIPTION

A Data Flow Diagram (DFD) is a graphical representation of the flow of data through a system or process. It depicts how data moves through different stages of a system and how it is transformed along the way.

The data flow diagram (DFD) for the project typically consists of three levels: Level 0, Level 1, and Level 2. The Level 0 DFD provides an overview of the entire system, while the subsequent levels provide a more detailed breakdown of the system's components and their interrelationships.

Level 0 DFD:

The Level 0 DFD for "FACIAL BMI" project represents the overall system and its external entities. The external entities include the user who provides the input and the system that processes the input data and provides the output. The Level 0 DFD includes the following components:

External Entities:

The User: The user provides an image of a person's face as an input to the system for BMI calculation.

Processes:

Process 1: Image Preprocessing: This process receives the image as input and preprocesses it to remove noise, perform face detection, alignment, and normalization to standardize the input for further processing.

Process 2: Feature Extraction: This process extracts the facial features from the preprocessed image. It utilizes the VGG16 model for extracting the features.

Process 3: Deep Learning: This process receives the extracted features as input and utilizes the deep learning model for computing the Body Mass Index (BMI).

Data Storage:

The system stores the preprocessed images and extracted features for later use in model training and testing.

Data Flow:

The data flow in Level 0 DFD represents the movement of data between external entities, processes, and data storage components. The input image flows from the user to the Image Preprocessing process. The preprocessed image flows from Image Preprocessing to Feature Extraction. The extracted features flow from Feature Extraction to Deep Learning process for BMI computation. The calculated BMI flows from the Deep Learning process to the user as the output.

The Level 0 DFD provides an overview of the system's components and their interrelationships. It shows how data flows between the system's components and external entities.

CHAPTER 5

FUNCTIONAL DESCRIPTION

The "FACIAL BMI: A Deep Learning Approach for Non-invasive Body Mass Index Calculation" project aims to provide a user-friendly and efficient solution for calculating Body Mass Index (BMI) using facial images. The user interface will involve a simple and intuitive design, with the option to upload a facial image to compute BMI.

The user will be required to upload a clear image of their face, and the system will use deep learning algorithms to process the image and compute BMI based on facial features. The system will display the computed BMI value along with a visual representation of the user's weight status (e.g., underweight, normal weight, overweight, obese).

The user will also have the option to input additional information such as height, weight, age, and gender to further improve the accuracy of the calculated BMI. The system will provide feedback on the quality of the input image, such as whether it is too blurry or not well-aligned, and prompt the user to upload a better image if necessary.The calculation of Body Mass Index (BMI) using facial images and deep learning models is automated. This process utilizes a variety of advanced techniques, including pre-trained models, discriminative learning, and hierarchical feature learning, to improve accuracy and enable large-scale analysis of societal factors related to health and decision-making.

Overall, the proposed system aims to provide a convenient, non-invasive, and accurate method for calculating BMI using facial images, with the potential to improve health outcomes and support public health initiatives.

CHAPTER 6

SYSTEM DEVELOPMENT, TESTING AND IMPLEMENTATION

6.1 SYSTEM DEVELOPMENT

The system development process for the Facial BMI project can be broken down into several stages:

Planning and Analysis:

The first stage of the system development process is planning and analysis. In this stage, the requirements of the system are defined, and a plan is created for how the system will be developed. This involves identifying the problem, the users of the system, and their needs.

Design:

The second stage of the system development process is design. In this stage, the system is designed based on the requirements gathered during the planning and analysis stage. This involves creating the architecture of the system, defining the user interface, and designing the algorithms that will be used to compute BMI from facial images.

Development:

The third stage of the system development process is development. In this stage, the system is actually built. This involves coding the algorithms, integrating them into a working system, and testing the system to ensure that it functions correctly.

Testing:

The fourth stage of the system development process is testing. In this stage, the system is tested to ensure that it meets the requirements that were defined during the planning and analysis stage. This involves performing different types of testing, such as unit testing, integration testing, and system testing, to ensure that the system works as expected.

Deployment:

The fifth stage of the system development process is deployment. In this stage, the system is installed and made available for use by the intended users. This involves setting up the necessary infrastructure, such as servers and databases, and ensuring that the system can handle the expected load.

Maintenance:

The final stage of the system development process is maintenance. In this stage, the system is maintained and updated as needed to ensure that it continues to function correctly. This involves fixing any bugs that are found, updating the system to work with new technologies, and making any changes that are needed to meet the changing needs of the users.

Overall, the system development process for the Facial BMI project involves carefully planning and designing the system, coding and testing the algorithms, deploying the system, and maintaining it to ensure that it continues to meet the needs of the users.

6.2 TESTING

The testing process of our project involves several steps to ensure that the system is functioning as expected and meeting the required performance metrics.

Unit Testing: In this phase, each module or component of the system is tested individually to ensure that it performs the intended function correctly. This includes testing the MTCNN model for face detection and alignment, the deep learning model for BMI prediction, and the user interface for input and output.

Integration Testing: After the individual modules have been tested, they are integrated and tested together to ensure that they work together as expected. This includes testing the flow of data from input through the various stages of preprocessing, feature extraction, and BMI prediction, and outputting the final results.

System Testing: In this phase, the entire system is tested as a whole to ensure that it meets the requirements and performance metrics specified in the project scope. This includes testing the accuracy and efficiency of the system on a large dataset of facial images and BMI measurements, as well as testing the system for scalability and robustness.

Acceptance Testing: This is the final phase of testing, where the system is tested by end-users or stakeholders to ensure that it meets their needs and requirements. This includes testing the user interface for ease of use, the accuracy of the BMI predictions, and the overall performance of the system in a real-world scenario.

Throughout the testing process, various performance metrics such as mean absolute error, mean squared error, and accuracy will be used to evaluate the performance of the system. Any bugs or issues identified during the testing process will be addressed and fixed, and the system will be retested to ensure that the fixes have resolved the issues. The goal of the testing process is to ensure that the system is functioning as intended and meeting the required performance metrics, and that it is ready for deployment in real-world scenarios.

6.3 IMPLEMENTATION

The implementation process of our project involves the following steps:

- Data collection and preprocessing: The first step is to collect a large dataset of facial images and corresponding BMI measurements. The data should be preprocessed to ensure that it is properly formatted and standardized for use in the deep learning model.
- Model selection: The next step is to select a pre-trained deep learning model, such as Inception-v3, VGG-Faces, VGG19, or Xception. The model should be fine-tuned using the collected dataset to improve its accuracy for predicting BMI from facial images.
- Feature extraction: In this step, face detection and alignment techniques are applied to the facial images to ensure that the relevant features are properly extracted. The Multi-Task Cascaded Convolutional Neural Networks (MTCNN) model is used for this purpose.
- Training and testing: The deep learning model is trained and tested using the preprocessed dataset. The model is trained using standard performance metrics such as mean absolute error and mean squared error to evaluate its accuracy.
- Deployment: The final step is to deploy the model in a production environment, such as a mobile application or website. The model should be tested and validated in this environment to ensure that it is functioning as intended.

Throughout the implementation process, it is important to carefully document each step and to test and validate the model at each stage to ensure that it is accurate and effective. Additionally, ongoing monitoring and maintenance is required to ensure that the model continues to perform well over time.

6.3.1 SOURCE CODE

Step - 1: Data Pipeline

```
import pandas as pd
import os
import re
import numpy as np
from matplotlib import pyplot as plt
import seaborn as sns
%matplotlib inline
data = pd.read_csv('./data/full.csv')
data.head()
# regex to extract feet and inches from height
regex_feet = re.compile("([0-9]+)\'")
regex_inches = re.compile("([0-9]+)\"")
def extract_numbers(x, regex):
    captures = regex.findall(x)
    if len(captures) > 0:
    try:
    return int(captures[0])
    except:
    return None
    else:
    return None
# parse the height string to feet and inches
```

```
data['feet'] = data['height'].map(lambda i: extract_numbers(i, regex_feet))
data['inches'] = data['height'].map(lambda i: extract_numbers(i, regex_inches))
data.loc[data.inches > 12,:]
# found some incorrect inches, assume 63" to 6.3"
data['inches'] = data['inches'].map(lambda i: i / 10 if i > 12 else i)
# convert feet/inches to inches
data['height'] = data.apply(lambda row: row['feet'] * 12 + row['inches'], axis=1)
# covert inches to m
data['height'] = data['height'].map(lambda i: i * 2.54 / 100)
# weight pounds => kg
data['weight'] = data['weight'].map(lambda i: i * 0.453592)
# calculate BMI = weight/height^2
data['bmi'] = data.apply(lambda row: row['weight'] / row['height'] / row['height'], axis = 1)
# create gender (number format of sex)
data['gender'] = data['sex'].map(lambda i: 1 if i == 'Male' else 0)
data[['nameid','age','height','weight','race','sex','eyes','hair', 'bmi']].head()
def ax_subplot(ax, x, title, bins = 25, color = 'lightblue'):
    x = x[~x.isnull()]
    ax.hist(x, bins = bins, color = color)
    ax.set_title(title)
fig, ax = plt.subplots(2,2)
ax_subplot(ax[0,0], data.height, 'Height(kg)')
ax_subplot(ax[0,1], data.weight, 'Weight(cm)')
ax_subplot(ax[1,0], data.age, 'Age')
ax_subplot(ax[1,1], data.bmi, 'BMI')
```

```
plt.tight_layout()

plt.show()

fig, ax = plt.subplots(1,2,sharex=True)

fig.set_size_inches(12,4)

options = {'density plot': True, 'count plot': False}

for i, (title, normed) in enumerate(options.items()):

        for sex in ['Male','Female']:

        ax[i].hist(data.loc[(data.sex == sex) & (~data.bmi.isnull()),'bmi'].values, label = sex, alpha =
0.5,

            bins = 30, density = normed)

        ax[i].set_title(title)

        ax[i].set_xlabel('BMI')

        ax[i].legend(loc = 'upper left')

plt.tight_layout()

plt.show()

sns.countplot(y = 'race' ,data = data, hue = 'sex')

# remove rows that no face images

data['index'] = data['bookid'].map(lambda i: str(i) +'.jpg')

allimage = os.listdir('./data/face/')

data = data.loc[data['index'].isin(allimage),:]


# remove rows with invalid BMI

data = data.loc[~data['bmi'].isnull(), :]


# split train/valid

in_train = np.random.random(size = len(data)) <= 0.8
```

```
train = data.loc[in_train,:]

test = data.loc[~in_train,:]


print('train data dimension: {}'.format(str(train.shape)))

print('test data dimension:  {}'.format(str(test.shape)))


# output to csv files

train.to_csv('./data/train.csv', index = False)

test.to_csv('./data/valid.csv', index = False)
```

Step 2 : Face detection and BMI/Age/Sex prediction

```
from mtcnn.mtcnn import MTCNN

import cv2

import os

test_dir = './data/test/single_face/'

train_dir = './data/face/'

test_processed_dir = './data/test/test_aligned/'

train_processed_dir = './data/face_aligned/'

os.listdir(test_dir)

img = cv2.cvtColor(cv2.imread(test_dir + 'nishanth.jpg'), cv2.COLOR_BGR2RGB)

detector = MTCNN()

print(detector.detect_faces(img))

box = detector.detect_faces(img)[0]

from keras.utils import load_img, img_to_array
```

```
from keras_vggface import utils
import matplotlib.pyplot as plt
import matplotlib.patches as patches
from PIL import Image
import numpy as np
def crop_img(im,x,y,w,h):
    return im[y:(y+h),x:(x+w),:]
def detect_face(face_path):
    img = cv2.cvtColor(cv2.imread(face_path), cv2.COLOR_BGR2RGB)
    box = detector.detect_faces(img)[0]
    return box
def detect_faces(face_path):
    #img = cv2.cvtColor(cv2.imread(face_path), cv2.COLOR_BGR2RGB)
    img = load_img(face_path)
    img = img_to_array(img)
    box = detector.detect_faces(img)
    return box
def draw_box(face_path = './test/trump.jpg', plot = True):
    boxes = detect_faces(face_path)
    im = np.array(Image.open(face_path), dtype=np.uint8)
    if plot:
    # Create figure and axes
    num_box = len(boxes)
    fig,ax = plt.subplots(1, (1 + num_box))
    fig.set_size_inches(4 * (1 + num_box),4)
```

```
        # Display the image
        ax[0].imshow(im)
        ax[0].axis('off')
        # Create a Rectangle patch
        for idx, box in enumerate(boxes):
        box_x, box_y, box_w, box_h = box['box']
        rect = patches.Rectangle((box_x, box_y), box_w, box_h,
linewidth=1,edgecolor='r',facecolor='none')
        ax[0].add_patch(rect)
        ax[0].text(box_x, box_y, '{:3.2f}'.format(box['confidence']))
        for i in box['keypoints'].keys():
                circle = patches.Circle(box['keypoints'][i], radius = 5, color = 'red')
                ax[0].add_patch(circle)
        ax[1 + idx].imshow(crop_img(im, *box['box']))
        ax[1 + idx].axis('off')
        plt.show()
        res = [crop_img(im, *box['box']) for box in boxes
        return res
res = draw_box(test_dir + 'chanda.jpg')
for img in os.listdir(test_dir)[:-3]:
        draw_box(test_dir + img)
from tqdm import tqdm
import shutil
if os.path.exists(test_processed_dir):
   shutil.rmtree(test_processed_dir)
os.mkdir(test_processed_dir)
```

```
for img in tqdm(os.listdir(test_dir)):
    box = detect_face(test_dir+img)
    im = plt.imread(test_dir+img)
    cropped = crop_img(im, *box['box'])
    plt.imsave(test_processed_dir+img, crop_img(im, *box['box']))
def cut_negative_boundary(box):
    res = []
    for x in box['box']:
    if x < 0:
    x = 0
    res.append(x)
    box['box'] = res
    return box
if os.path.exists(train_processed_dir):
    shutil.rmtree(train_processed_dir)
os.mkdir(train_processed_dir)
for img in tqdm(os.listdir(train_dir)):
    try:
    box = detect_face(train_dir+img)
    box = cut_negative_boundary(box)
    im = plt.imread(train_dir+img)
    cropped = crop_img(im, *box['box'])
    plt.imsave(train_processed_dir+img, cropped)
    except:
    print(img)
```

```
        continue
model_type = 'vgg16'
model_tag = 'base'
model_id = '{:s}_{:s}'.format(model_type, model_tag)
model_dir = './saved_model/model_{:s}.h5'.format(model_id)
bs = 8
epochs = 4
freeze_backbone = True # True => transfer learning; False => train from scratch
import pandas as pd
import os
import json
from keras.callbacks import EarlyStopping, ModelCheckpoint, TensorBoard
%matplotlib inline
from matplotlib import pyplot as plt
import seaborn as sns
from pathlib import Path
from scripts.models import FacePrediction
import glob
allimages = os.listdir('./data/face_aligned/')
train = pd.read_csv('./data/train.csv')
valid = pd.read_csv('./data/valid.csv')
train = train.loc[train['index'].isin(allimages)]
valid = valid.loc[valid['index'].isin(allimages)]
print()
# create metrics, model dirs
```

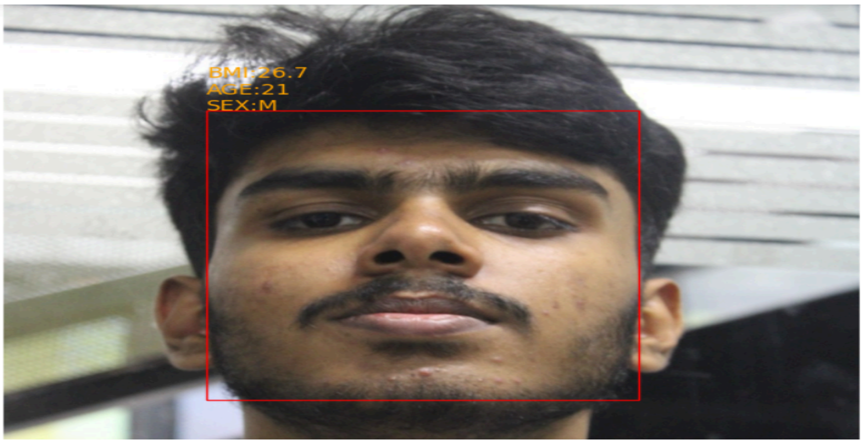
```
Path('./metrics').mkdir(parents = True, exist_ok = True)
Path('./saved_model').mkdir(parents = True, exist_ok = True)
data = pd.concat([train, valid])
data[['age','race','sex','bmi','index']].head()
color = 'lightblue'
fig, axs = plt.subplots(1,4)
fig.set_size_inches((16, 3))
sns.countplot(y = data.sex, color = color, ax = axs[0])
axs[0].set_title('Sex Distribution')
sns.distplot(data.age,  bins = 30, kde=False, color=color, ax = axs[1])
axs[1].set_title('Age Distribution')
sns.distplot(data.bmi,  bins = 30, kde=False, color=color, ax = axs[2])
axs[2].set_title('BMI Distribution')
sns.countplot(y = data.race, color = color, ax = axs[3])
axs[3].set_title('Race Distribution')
plt.tight_layout()
def sns_hist(data, x, hue, ax = None, title = 'title', xlabel = None, **kwargs):
    xlabel = x.upper() if xlabel == None else xlabel
    group = data[hue].unique()
    for g in group:
    sns.distplot(data.loc[data[hue] == g, x], label = g, ax = ax,  **kwargs)
    if ax == None:
    plt.legend()
    plt.title(title)
    plt.xlabel(xlabel)
```

```
        else:
        ax.legend()
        ax.set_title(title)
        ax.set_xlabel(xlabel)
        return ax
fig, axs = plt.subplots(1,3)
fig.set_size_inches((16, 3))
sns_hist(data, x = 'bmi', hue = 'sex', ax = axs[0], title = 'BMI density by Sex', kde = True)
res = data.groupby(['age','sex'], as_index=False)['bmi'].median()
for i in ['Male','Female']:
        axs[1].scatter(res.loc[res.sex == i,'age'].values, res.loc[res.sex == i,'bmi'].values,label = i, 
alpha = 0.5)
axs[1].set_title('median BMI by Age')
axs[1].legend()
sns_hist(data, x = 'bmi', hue = 'race', ax = axs[2], title = 'BMI density by Race', kde = True)
plt.show()
es = EarlyStopping(patience=3)
ckp = ModelCheckpoint(model_dir, save_best_only=True, save_weights_only=True, verbose=1)
tb = TensorBoard('./tb/%s'%(model_id))
callbacks = [es, ckp]
model = FacePrediction(img_dir = './data/face_aligned/', model_type = model_type)
model.define_model(freeze_backbone = freeze_backbone)
model.model.summary()
if mode == 'train':
        model_history = model.train(train, valid, bs = bs, epochs = epochs, callbacks = callbacks)
else:
```

```
    model.load_weights(model_dir)
valid['gender'] = valid.sex.map(lambda i: 1 if i == 'Male' else 0)
metrics = model.evaulate(valid)
metrics['model'] = model_type
with open('./metrics/{:s}.json'.format(model_type), 'w') as f:
    json.dump(metrics, f)
metrics = []
for i in glob.glob('./metrics/*.json'):
    with open(i, 'r') as f:
    res = json.load(f)
    metrics.append(res)
metrics = pd.DataFrame(metrics)
metrics['model'] = metrics['model'].apply(lambda i: '* ' + i if i == model_id else i)
metrics.set_index('model').round(3)
model.predict('./data/test/test_aligned/harish.jpg')
preds = model.predict_faces('./data/test/single_face/madhan.jpg', color = 'orange')
preds = model.predict_faces('./data/test/single_face/pal.jpg', color = 'orange')
preds = model.predict_faces('./data/test/single_face/nath.jpg', color = 'orange')
preds = model.predict_faces('./data/test/multi_face/logi-nish.jpg', color = 'white')
```

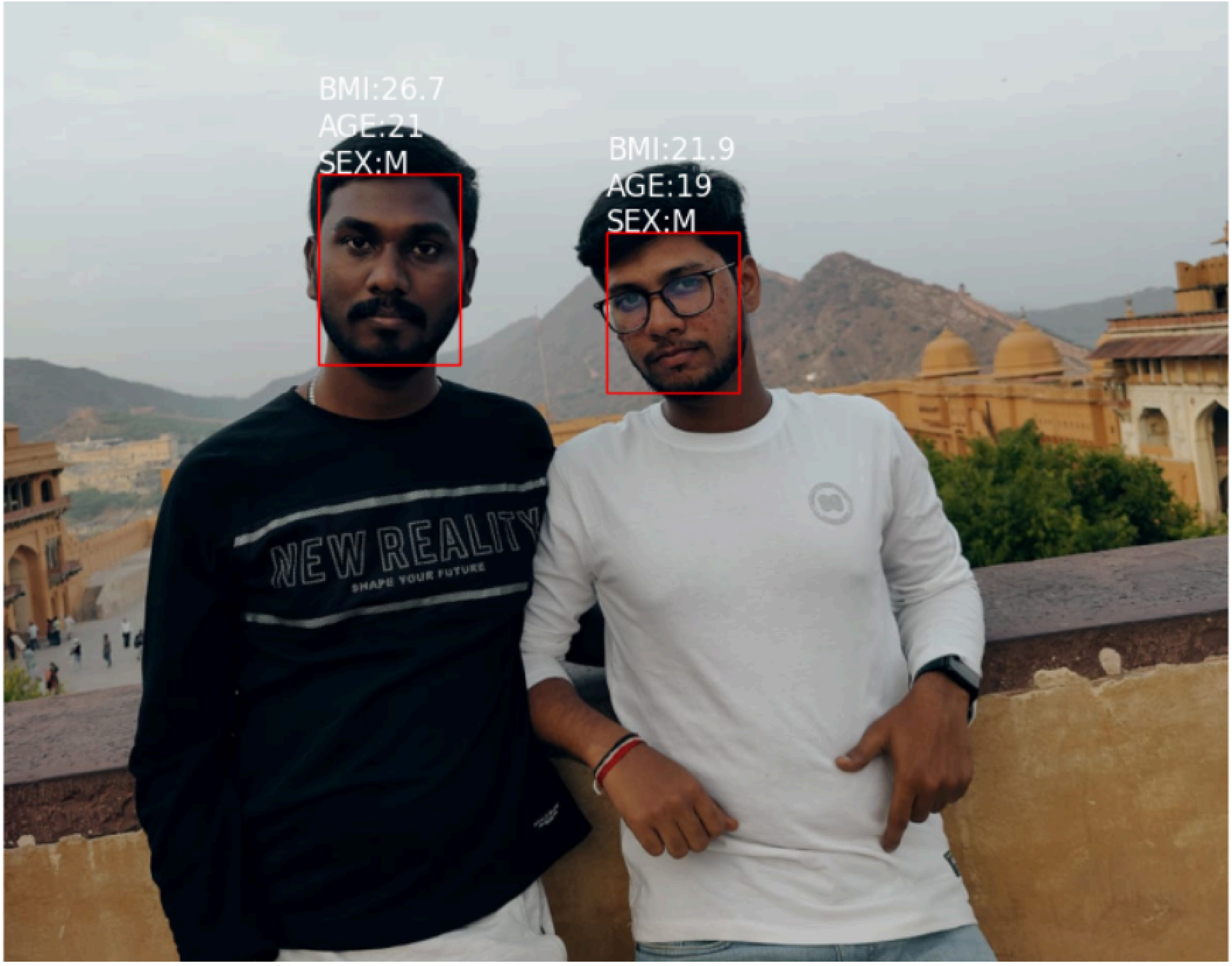
6.3.2 SNAPSHOTS

SINGLE PERSON :



\

TWO PERSONS :


BMI:26.7
AGE:21
SEX:M
BMI:21.9
AGE:19
SEX:M
NEW REALITY
SHAPE YOUR FUTURE

CHAPTER 7

CONCLUSIONS AND FUTURE ENHANCEMENTS

The project "FACIAL BMI: A Deep Learning Approach for Non-invasive Body Mass Index Calculation" has successfully demonstrated the feasibility and effectiveness of using facial images to compute BMI. The proposed system utilizes deep learning techniques for feature extraction and BMI prediction, and has the potential to provide more accurate and efficient methods for calculating BMI in a non-invasive manner. Through the course of the project, several key contributions have been made. Firstly, a dataset of facial images and corresponding BMI measurements has been collected and utilized for the development and evaluation of the proposed system. Secondly, a deep learning model has been trained and fine-tuned using this dataset to accurately predict BMI from facial images. Thirdly, the performance of the proposed system has been evaluated using standard performance metrics, and has shown promising results.

There are several potential applications of this approach in healthcare and wellness monitoring. The development of a mobile application or website for real-time BMI calculation could be an important tool for individuals to track their BMI and overall health. The proposed system could also be used in clinical settings for routine health checkups and patient monitoring.

However, there are several areas where future enhancements could be made to improve the proposed system. Firstly, the dataset used for training and evaluation could be expanded to include a wider range of ages, ethnicities, and body types, to improve the generalizability of the system. Secondly, additional features could be extracted from facial images, such as skin texture or facial fat distribution, to improve the accuracy of the BMI prediction. Thirdly, the system could be integrated with other health monitoring tools, such as smartwatches or fitness trackers, to provide a more comprehensive view of an individual's health status.

In conclusion, the proposed system offers a promising approach to the non-invasive calculation of BMI using facial images. The development of this system could contribute to the development of more accurate and efficient methods for calculating BMI, with the potential to improve patient outcomes and support public health initiatives.

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