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Estimating Body Mass Index from Facial Images

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Abstract: A person's health status may have a significant impact on many aspects of their life, from mental health to lifespan to financial security. The health of a person can be calculated by a value which is called Body Mass Index (BMI), it uses both the height and weight of a person. Numerous variables, including physical health, mental health, and popularity, have been linked to BMI. With the increasing number of people being obese, self-diagnostic solutions for healthy weight monitoring are grabbing significant attention. Calculating BMI using the statistical formula requires precise measurements of the height and weight of a person and is time-consuming. The main objective of this project is to predict the BMI of a person by giving the image as input. While developing Fitness apps, we can use this system to detect the BMI of a person daily and suggest suitable exercises. The developed system can also be used to find whether a person is suffering from malnutrition and some other diseases that can be detected using BMI. The models used in our project are FaceNet, Ridge Linear Regression, Random Forest Regression, Support Vector Regression, and ensemble of regression models.
Keywords: Body Mass Index, Computer Vision, Regression, Face Recognition, Ensemble algorithms

I. INTRODUCTION

The emergence of machine learning techniques coupled with computer vision has revolutionized various fields, from biometrics to healthcare. In this era of digital transformation, the ability to extract meaningful insights from visual data opens up new avenues for understanding human physiology and behavior. One such endeavor is the prediction of anthropometric measures—height, weight, and Body Mass Index (BMI)—from facial images using machine learning regression.

Anthropometric measures serve as fundamental indicators of an individual's health status, providing valuable insights into their physical well-being. Traditionally, these measures are obtained through direct measurements or self-reported data, which can be intrusive, time-consuming, and prone to inaccuracies. However, recent advancements in computer vision and machine learning offer a promising alternative: predicting these measures non-invasively and automatically from facial images.

This project aims to explore the feasibility and efficacy of using facial images as a proxy for estimating height, weight, and BMI. By leveraging the intricate patterns and features encoded within facial structures, machine learning regression models can potentially infer anthropometric measures with reasonable accuracy. Such an approach not only offers convenience but also has the potential to revolutionize various domains, including healthcare, fitness tracking, and biometrics.

The proposed work will involve the development of a robust machine learning regression model trained on a diverse dataset encompassing facial images annotated with corresponding height, weight, and BMI information. Through feature extraction techniques and sophisticated regression algorithms, the model will learn to establish predictive relationships between facial characteristics and anthropometric measures. Furthermore, techniques such as data augmentation and regularization will be employed to enhance the model's generalizability and robustness across diverse demographic profiles.

The outcomes of this project hold immense promise for real-world applications. Accurate prediction of height, weight, and BMI from facial images can facilitate personalized healthcare interventions, enable more effective fitness monitoring, and contribute to the development of innovative biometric identification systems. Moreover, by exploring the relationship between facial morphology and anthropometric measures, this project seeks to advance our understanding of human physiology and pave the way for novel approaches in health assessment and biometric authentication.

II. LITERATURE REVIEW

The intersection of computer vision, machine learning, and healthcare has opened new avenues for innovative research aimed at leveraging facial images for predictive modeling of anthropometric measures such as height, weight, and Body Mass Index (BMI). In this context, this project delves into the exploration of predicting these essential health indicators solely from facial images using machine learning regression techniques.

The concept of predicting anthropometric measures from facial images has garnered significant attention in recent years, driven by advancements in both computer vision and machine learning algorithms. Several studies have explored various approaches and methodologies to achieve accurate predictions, contributing to the growing body of knowledge in this domain.

One notable line of research focuses on feature extraction and representation learning from facial images. Early studies often relied on handcrafted features such as facial landmarks, texture descriptors, and geometric ratios to characterize facial morphology. For instance, *Hu et al. (2016)* utilized facial landmarks and geometric ratios to estimate BMI from facial images with promising results. Similarly, *Liu et al. (2019)* proposed a method based on facial landmarks and texture features to predict both weight and BMI.

By Lingyun Wen, Guodong Guo. (2013), The framework they proposed involves face detection, aligning images of all faces by face normalization, then using ASM (Active Shape Model) to detect reference points in each image.

Ivan William, De Rosal Ignatius Moses Setiadi, Eko Hari Rachmawanto, Heru Agus Santoso, Christy Atika Sar. (2019), Google created the Facenet architecture to recognise and identify faces in images. I. William et al., justified that face net provides more accuracy than CASIA-WebFace and VGGFace2, when they are compared. For testing, they made use of publicly accessible data sets like YALE, JAFFE, AT&T, Georgia Tech, and Essex.

With the advent of deep learning, convolutional neural networks (CNNs) have emerged as powerful tools for automatic feature extraction from images. Deep learning-based approaches have shown remarkable success in various computer vision tasks, including facial analysis and recognition. Researchers have employed CNN architectures to learn discriminative features directly from facial images for predicting anthropometric measures. For instance, Liu et al. (2020) proposed a deep neural network framework that directly regresses height, weight, and BMI from facial images, achieving superior performance compared to traditional methods.

Furthermore, the availability of large-scale annotated datasets has played a crucial role in advancing research in this field. Datasets such as the Multi-ethnicity Aged Faces (MAFA) dataset and the SCUT-FBP5500 dataset provide diverse facial images annotated with anthropometric measures, facilitating the development and evaluation of predictive models. Additionally, efforts have been made to address challenges related to dataset bias and generalization across different demographics and ethnicities.

Despite the progress made, several challenges remain in predicting anthropometric measures from facial images. These include handling variations in facial expressions, poses, and lighting conditions, as well as addressing issues related to privacy and ethical considerations in handling sensitive health-related data.

In summary, the literature highlights the potential of using machine learning regression techniques to predict height, weight, and BMI from facial images.

Through a review of existing studies, this project aims to build upon previous work, exploring novel methodologies and approaches to enhance the accuracy and robustness of predictive models, ultimately contributing to advancements in personalized healthcare and biometric identification systems.

III. METHODOLOGY

The project aims to develop accurate and reliable machine learning regression models for predicting height, weight, and BMI from facial images, contributing to advancements in personalized healthcare and biometric identification systems.

A. Data Collection and Preprocessing

1) Gathered a diverse dataset of facial images annotated with corresponding height, weight, and BMI measurements. Ensure the dataset represents various demographics, including different age groups, genders, and ethnicities.
2) Preprocessed the facial images to enhance quality and standardize features. This includes tasks such as labeling, resizing, cropping, and normalization to mitigate variations in lighting, pose, and facial expression.
3) Split the dataset into training, validation, and testing sets to evaluate model performance effectively.

B. Feature Extraction

1) Utilized both traditional and deep learning-based methods for feature extraction.
2) Worked on traditional methods may involve extracting facial landmarks, texture descriptors, and geometric ratios from the facial images.
3) Incorporated Face Net , face recognition for facial feature encoding

C. Model Development

1) Explored various regression algorithms suitable for predicting continuous variables like height, weight, and BMI. Common choices include linear regression, support vector regression (SVR), decision trees, and ensemble methods like random forests or gradient boosting.
2) Developed and train machine learning regression models using the extracted features as input and the corresponding height, weight, and BMI measurements as targets.
3) Experiment with different architectures and hyper parameters to optimize model performance. Regularization techniques such as pruning applied to prevent over fitting.

D. Model Evaluation

1) Evaluated the trained models on the validation set to assess their performance in predicting height, weight, and BMI.
2) Measured performance metrics such as mean squared error (MSE), mean absolute error (MAE), and coefficient of determination (R-squared) to quantify the accuracy of predictions.
3) Fine-tune the models based on validation performance, adjusting hyper parameters and exploring alternative architectures as necessary.

E. Testing and Validation

1) Assessed the final trained models on the independent testing set to evaluate their generalization ability.
2) Compare the predicted anthropometric measures with ground truth values to validate the reliability and robustness of the models.

F. Ethical Considerations

1) Ensured compliance with ethical guidelines and data protection regulations when collecting, handling, and analyzing facial images and associated health-related data.

IV. MACHINE LEARNING REGRESSION ALGORITHMS

Machine learning regression is a branch of supervised learning where the goal is to predict a continuous target variable based on one or more input features. Regression algorithms are widely used in various fields, including healthcare, finance, economics, and engineering. The developed project worked on the following listed algorithms.

A. Face Net

1) Face Net is a deep learning model specifically designed for facial recognition tasks. It uses a deep convolution neural network (CNN) to extract high-dimensional feature embeddings from facial images.
2) The key idea behind Face Net is to learn a mapping from facial images to a compact Euclidean space where distances directly correspond to a measure of face similarity.
3) By training on large datasets of labeled facial images, Face Net learns to generate embeddings that effectively capture facial characteristics and can be used for tasks such as face verification, clustering, and classification.
4) In the context of predicting height, weight, and BMI from face images, FaceNet can be used for feature extraction, where the extracted facial embeddings serve as input features for regression algorithms.

B. Ridge Linear Regression

1) Ridge regression is a linear regression technique that aims to mitigate multicollinearity (high correlation among predictor variables) and reduce model complexity by adding a regularization term to the standard linear regression objective function.
2) The regularization term penalizes large coefficients, effectively shrinking them towards zero and preventing over fitting.
3) In the context of predicting anthropometric measures from face images, Ridge linear regression can be applied to model the relationship between extracted facial features and height, weight, and BMI.
4) It provides a straightforward and interpretable approach to regression while handling multicollinearity and preventing over fitting.

C. Random Forest Regression

1) Random forest regression is an ensemble learning technique based on decision trees, where multiple decision trees are trained independently and their predictions are aggregated to produce the final output.
2) Each decision tree is trained on a random subset of the data and a random subset of features, introducing randomness and diversity among the trees.
3) Random forest regression is robust to over fitting and capable of capturing complex nonlinear relationships between input features and target variables.
4) In the context of predicting anthropometric measures from face images, random forest regression can effectively handle high-dimensional feature spaces and nonlinear relationships, making it a suitable choice for modeling complex facial characteristics.

D. Support Vector Regression (SVR)

1) Support vector regression is a supervised learning algorithm that extends the principles of support vector machines (SVMs) to regression tasks.
2) SVR aims to find a hyper plane that best fits the training data while minimizing the margin violations, where the margin represents the tolerance for error.
3) SVR is particularly effective in high-dimensional spaces and is robust to outliers due to the use of a loss function that penalizes errors outside a certain margin.
4) In the context of predicting height, weight, and BMI from face images, SVR can be used to model the relationship between facial features and anthropometric measures while handling high-dimensional feature spaces and outliers effectively.

E. Ensemble of Regression Models - Extended Gradient Boosting Algorithm (E.G., XGBOOST)

1) Gradient boosting is an ensemble learning technique that builds a strong predictive model by combining the predictions of multiple weak learners, typically decision trees.
2) The key idea behind gradient boosting is to sequentially train new models to correct the errors made by previous models, focusing on the examples that are difficult to predict.
3) XGBoost (Extreme Gradient Boosting) is a popular implementation of gradient boosting known for its efficiency and scalability, using a regularized objective function and parallelized tree construction.
4) In the context of predicting anthropometric measures from face images, an ensemble of regression models such as XGBoost can effectively capture complex relationships between facial features and height, weight, and BMI, leading to improved predictive performance.

Overall, each of these machine learning algorithms offers unique advantages and capabilities that can be leveraged to predict height, weight, and BMI from face images, depending on the specific requirements and characteristics of the dataset. Experimentation and comparative analysis can help determine the most suitable algorithm or combination of algorithms for the task at hand.

V. EXPERIMENTAL RESULTS

Creating a dataset for predicting height, weight, and BMI from facial images using machine learning regression involves several key considerations:

1) *Data Collection:* Gather a diverse dataset of facial images along with corresponding height, weight, and BMI measurements. Ensure that the dataset includes individuals from various demographic groups, including different age ranges, genders, ethnicities, and body types, to capture the full spectrum of facial variations and anthropometric measures.
2) *Annotation:* Annotate each facial image with the corresponding height, weight, and BMI measurements. This annotation process may involve manual measurements or the use of self-reported data, depending on the availability and reliability of the information.
3) *Data Quality and Consistency:* Ensure that the facial images are of high quality and resolution, with consistent lighting, background, and pose across the dataset. Poor-quality images or images with significant variations in lighting, pose, or facial expression can adversely affect the performance of the regression model
4) *Privacy and Ethical Considerations:* Respect privacy and ethical considerations when collecting and handling facial image data, particularly when dealing with sensitive health-related information such as height, weight, and BMI. Obtain informed consent from participants and anonymize or de-identify the data to protect individuals' privacy.

5) *Dataset Balance:* Ensure that the dataset is balanced with respect to different demographic groups and anthropometric measures to prevent biases in the regression model. Strive for equal representation of diverse populations to ensure the model's generalizability and fairness.
6) *Data Splitting:* Divide the dataset into training, validation, and testing sets to evaluate the performance of the regression model effectively. The training set is used to train the model, the validation set is used to tune hyper parameters and monitor performance during training, and the testing set is used to assess the model's generalization ability on unseen data.
7) *Data Augmentation:* Consider augmenting the dataset through techniques such as rotation, flipping, scaling, and adding noise to increase the diversity of facial images and improve the robustness of the regression model.
8) *Data Preprocessing:* Preprocess the facial images to enhance quality and standardize features. This may include tasks such as resizing, cropping, normalization, and grayscale conversion to mitigate variations in lighting, pose, and facial expression.

By carefully crating and preparing a facial image dataset with these considerations in mind, you can develop a robust machine learning regression model to predict height, weight, and BMI from facial images effectively.

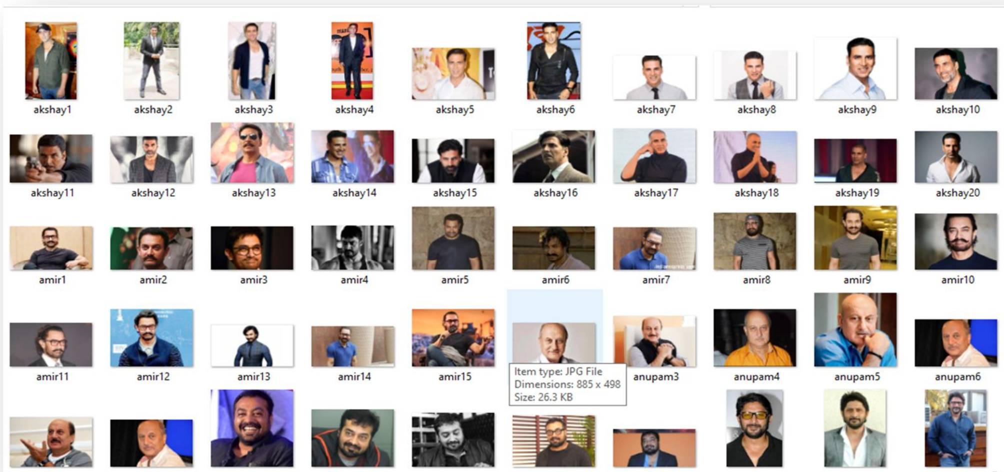


Fig – 1: Sample dataset

VI. MODELS PERFORMANCE REPORTS

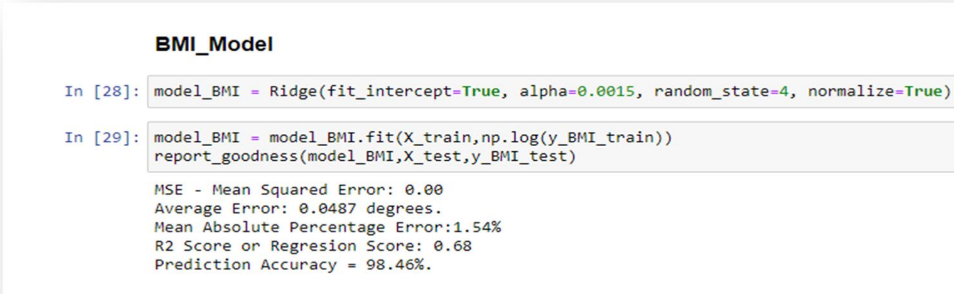
1) *Face NET - FACE Feature Encoding | Face Recognition*

BMI_Model

```
In [22]: model_BMI = linear_model.LinearRegression()
         model_BMI = model_BMI.fit(X_train,np.log(y_BMI_train))

In [23]: print("EVALUATION REPORT - BMI MODEL")
         print("------------------------------")
         report_goodness(model_BMI,X_test,y_BMI_test)

         EVALUATION REPORT - BMI MODEL
         ------------------------------
         MSE - Mean Squared Error: 0.01
         Average Error: 0.0733 degrees.
         Mean Absolute Percentage Error:2.33%
         R2 Score or Regresion Score: 0.27
         Prediction Accuracy = 97.67%.
```

Fig – 2: Evaluation Report of Face Net - Face Feature Encoding | Face Recognition

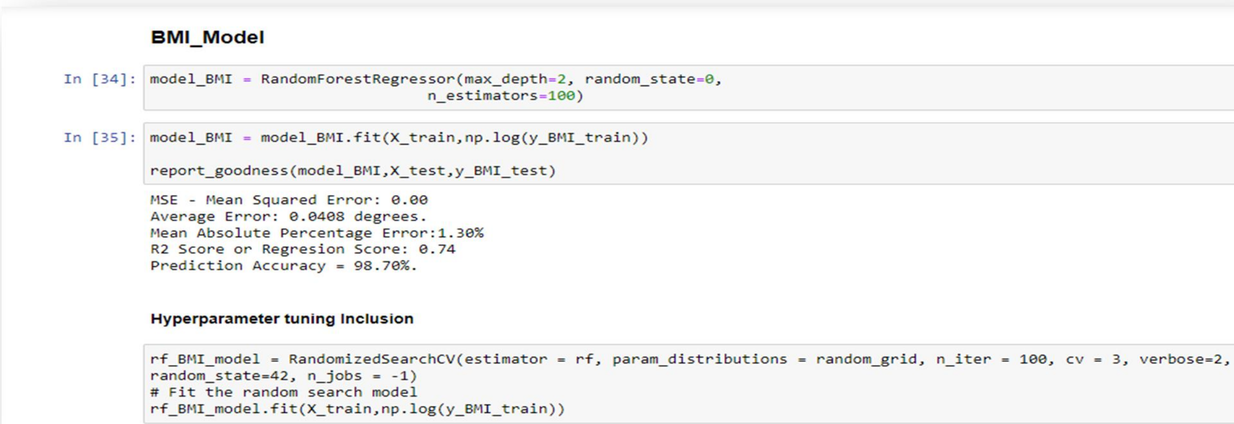
2) Ridge Linear Regression



```
BMI_Model

In [28]: model_BMI = Ridge(fit_intercept=True, alpha=0.0015, random_state=4, normalize=True)

In [29]: model_BMI = model_BMI.fit(X_train,np.log(y_BMI_train))
         report_goodness(model_BMI,X_test,y_BMI_test)

         MSE - Mean Squared Error: 0.00
         Average Error: 0.0487 degrees.
         Mean Absolute Percentage Error:1.54%
         R2 Score or Regresion Score: 0.68
         Prediction Accuracy = 98.46%.
```

Fig – 3: Evaluation Report of Ridge Linear Regression

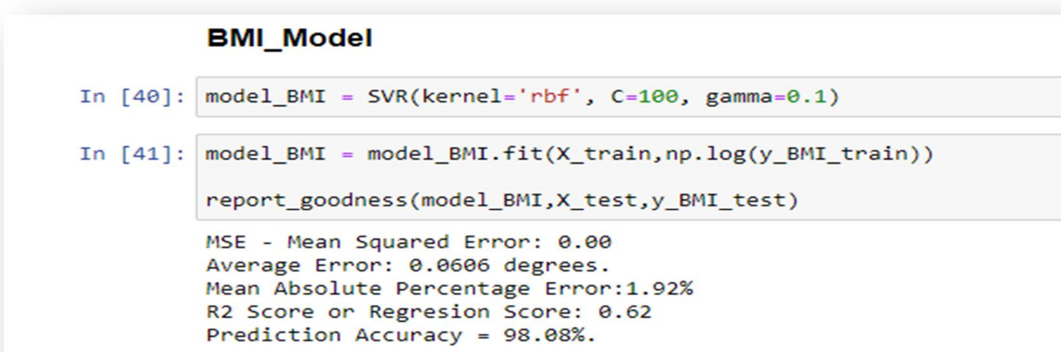
3) Random Forest Regression - Ensemble Regression Algorithm- (Bagging Approach)



```
BMI_Model

In [34]: model_BMI = RandomForestRegressor(max_depth=2, random_state=0,
                                           n_estimators=100)

In [35]: model_BMI = model_BMI.fit(X_train,np.log(y_BMI_train))

         report_goodness(model_BMI,X_test,y_BMI_test)

         MSE - Mean Squared Error: 0.00
         Average Error: 0.0408 degrees.
         Mean Absolute Percentage Error:1.30%
         R2 Score or Regresion Score: 0.74
         Prediction Accuracy = 98.70%.

Hyperparameter tuning Inclusion

rf_BMI_model = RandomizedSearchCV(estimator = rf, param_distributions = random_grid, n_iter = 100, cv = 3, verbose=2,
random_state=42, n_jobs = -1)
# Fit the random search model
rf_BMI_model.fit(X_train,np.log(y_BMI_train))
```

Fig – 4: Evaluation Report of Random Forest Regression

4) Support Vector Machine Regression



```
BMI_Model

In [40]: model_BMI = SVR(kernel='rbf', C=100, gamma=0.1)

In [41]: model_BMI = model_BMI.fit(X_train,np.log(y_BMI_train))

         report_goodness(model_BMI,X_test,y_BMI_test)

         MSE - Mean Squared Error: 0.00
         Average Error: 0.0606 degrees.
         Mean Absolute Percentage Error:1.92%
         R2 Score or Regresion Score: 0.62
         Prediction Accuracy = 98.08%.
```

Fig – 5: Evaluation Report of Support Vector Machines

5) Ensemble Regression - (Boosting Approach)

BMI_Model

```
In [45]: xg_bmi = XGBRegressor(n_estimators=1000, max_depth=7, eta=0.1, subsample=0.7, colsample_bytree=0.8)
         xg_bmi = xg_bmi.fit(X_train,np.log(y_BMI_train))
         report_goodness(xg_bmi,X_test,y_BMI_test)

         MSE - Mean Squared Error: 0.00
         Average Error: 0.0282 degrees.
         Mean Absolute Percentage Error:0.91%
         R2 Score or Regresion Score: 0.84
         Prediction Accuracy = 99.09%.
```

Fig – 6: Evaluation Report of Ensemble Regression

6) Prediction | Test Results On Development Server

Manual Image Selection

```
In [49]: from IPython.display import Image

In [50]: test_image = 'test_data/vikky3.jpg'
         Image(test_image)

Out[50]:
```

```
In [51]: predict_height_weight_BMI(test_image,height_model,weight_model,bmi_model)

         test_data/vikky3.jpg

Out[51]: {'height': 1.8097211545207155,
          'weight': 81.17420010625314,
          'bmi': 24.785329201149388}
```

Fig – 7: Predictions on test samples

7) *Prediction | Test Results on Web Deployed Serving – Dr. APJ Abdul Kalam*

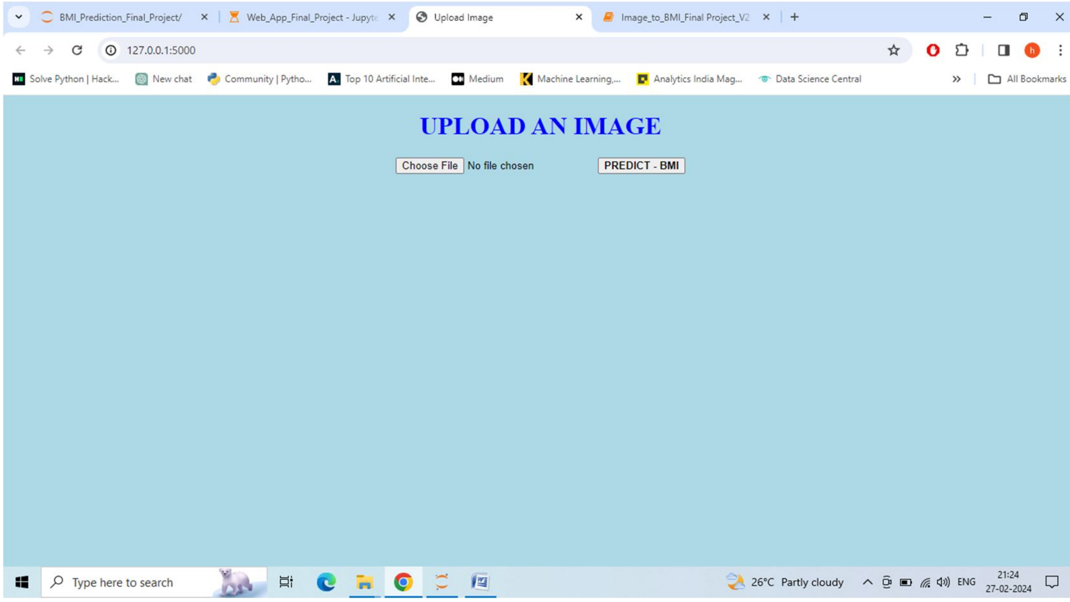


Fig – 8: Prediction Home page

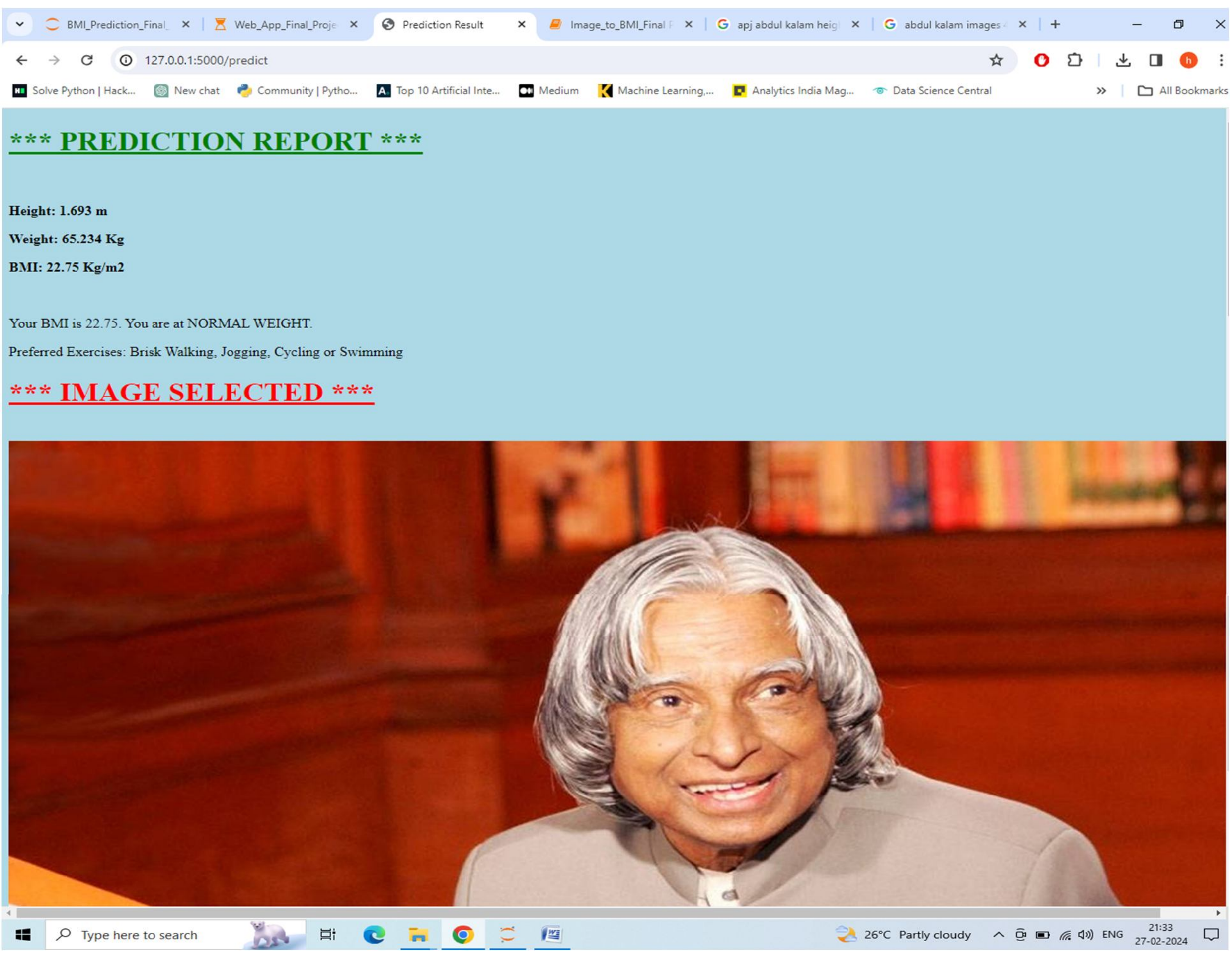


Fig – 9: Prediction Result: height: 1.693m, Weight: 65.23Kg, BMI: 22.75Kg/m2
Reference: https://starsunfolded.com/dr-apj-abdul-kalam/
Actual Metrics (As per Internet Resources: height: 1.63m, Weight: 60.23Kg, BMI: 22.64 Kg/m2)

VII. STRENGTHS AND LIMITATIONS OF THE STUDY

A. *Strengths of The System*

1) *Non-invasive Health Assessment:* The use of facial images for predicting height, weight, and BMI offers a non-invasive and accessible approach to health assessment, which can be particularly beneficial for individuals who may have limited access to traditional health assessment methods or prefer non-invasive alternatives.
2) *Personalized Health Monitoring:* The predictive model developed in the study can enable personalized health monitoring by providing individuals with estimates of their height, weight, and BMI based on facial images captured using common devices such as smart phones. This facilitates proactive health management and empowers individuals to track their health metrics conveniently.
3) *Potential for Early Detection of Health Issues:* By enabling regular monitoring of height, weight, and BMI from facial images, the study may contribute to the early detection of changes in health status or trends indicative of underlying health issues. Early detection can lead to timely interventions and preventive measures, potentially improving health outcomes.
4) *Cross-Domain Applications:* The study's findings and methodologies have potential applications beyond healthcare, including biometric identification systems, population health studies, and interdisciplinary research collaborations. This interdisciplinary approach can foster innovation and generate novel insights into the relationship between facial morphology and health-related metrics.
5) *Contribution to Research and Knowledge:* The study contributes to the growing body of research at the intersection of computer vision, machine learning, and healthcare. By exploring novel methodologies for predicting anthropometric measures from facial images, the study advances scientific understanding and opens up new avenues for research and development in personalized healthcare.

B. *Limitations Of The Prediction System*

1) *Generalizability and Bias:* The predictive model developed in the study may exhibit biases or limitations in generalizability due to factors such as dataset bias, demographic representation, and variations in facial morphology across populations. Due to limited computing resources worked on selective size dataset of human face and is extendable with the inclusion of image classification algorithms to predict any class of image with identifiable validations by the intervention with advanced computing resources.
2) *Data Quality and Availability:* The accuracy and reliability of the predictive model depend heavily on the quality and availability of the facial image dataset, as well as the accuracy of the annotations for height, weight, and BMI.
3) *Ethical and Privacy Considerations:* The use of facial image data for predicting health-related metrics raises ethical and privacy considerations, including concerns related to informed consent, data security, and potential misuse of sensitive health information. It is essential to address these considerations and adhere to ethical guidelines to protect individuals' rights and privacy.
4) *Interpretability and Explain Ability:* The predictive model developed using machine learning regression techniques may lack interpretability and explain ability, making it challenging to understand the underlying factors driving the model's predictions. Enhancing model interpretability can facilitate trust, transparency, and acceptance of the model in real-world applications.
5) *Validation and Evaluation:* The study's findings and predictive model should be rigorously validated and evaluated using appropriate metrics and validation techniques. This includes assessing the model's performance on independent datasets, conducting sensitivity analyses, and evaluating its robustness to variations in input data and model parameters.

VIII. FUTURE DIRECTIONS

The project to predict height, weight, and BMI from face images using machine learning regression holds significant potential for future advancements and applications. Here are some potential future scopes for the project:

1) *Integration with Healthcare Systems:* Collaborate with healthcare providers and institutions to integrate the developed predictive model into electronic health records (EHR) systems. This integration can enable healthcare professionals to utilize facial images as a non-invasive tool for health assessment and monitoring, facilitating personalized healthcare interventions and early detection of health-related issues.
2) *Mobile Applications for Health Monitoring:* Develop mobile applications that utilize the predictive model to estimate height, weight, and BMI from facial images captured using smartphone cameras. These applications can empower individuals to track their health metrics conveniently and regularly, promoting self-awareness and proactive health management.

3) *Population Health Studies:* Conduct population health studies leveraging the predictive model to analyze trends and patterns in height, weight, and BMI distributions across different demographic groups and geographical regions. These studies can provide valuable insights into public health challenges and inform targeted interventions to address disparities in health outcomes.
4) *Enhanced Biometric Identification Systems:* Explore applications of the predictive model in biometric identification systems for identity verification and authentication purposes. By incorporating facial image-based predictions of height, weight, and BMI, these systems can improve accuracy and robustness, particularly in scenarios where traditional biometric modalities may be insufficient or unreliable.
5) *Longitudinal Health Monitoring:* Extend the predictive model to support longitudinal health monitoring by tracking changes in height, weight, and BMI over time based on sequential facial images. This capability can facilitate early detection of changes in health status and enable timely interventions to prevent or manage health conditions effectively.
6) *Cross-Domain Collaborations:* Collaborate with researchers and practitioners from diverse domains such as nutrition science, psychology, and public health to explore interdisciplinary applications and implications of the predictive model. Cross-domain collaborations can foster innovation and generate novel insights into the complex interplay between facial morphology, anthropometric measures, and health outcomes.
7) *Ethical and Privacy Considerations:* Address ethical and privacy considerations associated with the use of facial image data for predicting health-related metrics. Develop robust privacy-preserving techniques and frameworks to ensure data security, informed consent, and protection of individuals' rights and confidentiality.

By pursuing these future scopes, the project can contribute to advancements in personalized healthcare, biometric technology, and population health management, ultimately improving health outcomes and enhancing quality of life for individuals and communities.

IX. CONCLUSION

In conclusion, the project to predict height, weight, and BMI from facial images using machine learning regression represents a significant advancement at the intersection of computer vision, machine learning, and healthcare. Through the exploration of novel methodologies and techniques, this project has demonstrated the feasibility and potential of using facial images as a non-invasive tool for health assessment and monitoring. By leveraging machine learning regression algorithms, the project has developed predictive models capable of estimating height, weight, and BMI from facial features extracted from images. These models offer a non-invasive and accessible approach to health assessment, empowering individuals to track their health metrics conveniently and proactively. The project's findings hold promise for various applications, including personalized healthcare, biometric identification systems, population health studies, and interdisciplinary research collaborations. Furthermore, the project contributes to the growing body of knowledge in personalized medicine, computer-aided diagnosis, and digital health technologies.

However, it is essential to acknowledge the limitations and challenges associated with the project, including concerns related to data quality, generalizability, ethical considerations, and model interpretability. Addressing these challenges and advancing research in these areas will be crucial for realizing the full potential of facial image-based health assessment techniques.

Moving forward, future research directions may include refining predictive models, addressing biases and limitations, validating findings on diverse populations, and exploring interdisciplinary collaborations to further enhance the impact and applicability of facial image-based health assessment technologies. In summary, the project represents a significant step towards harnessing the power of machine learning and computer vision to revolutionize healthcare delivery, empower individuals to take control of their health, and pave the way for personalized, accessible, and proactive health management solutions.

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