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"Age Estimation and Gender Detection"

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Master of Technology
in
Data Science and
Machine Learning

UE20CS972 – Project Phase - 2

Submitted by:

Tejonidhi S **PES2PGE21DS264**

Under the guidance of

Sudha B G
Faculty & Senior Manager,
Great Learning

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
FACULTY OF ENGINEERING
PES UNIVERSITY
(Established under Karnataka Act No. 16 of 2013)
Electronic City, Hosur Road, Bengaluru – 560 100, Karnataka, India

PES UNIVERSITY

(Established under Karnataka Act No. 16 of 2013)
Electronic City, Hosur Road, Bengaluru – 560 100, Karnataka, India

FACULTY OF ENGINEERING

CERTIFICATE

This is to certify that the dissertation entitled

Malicious URL detection and threat identification using lexicographic features

is a bonafide work carried out by

Tejonidhi S *PES2PGE21DS264*

In partial fulfilment for the completion of Fourth Semester Project Phase - 2 (UE20CS972) in the Program of Study - Master of Technology in Data Science and Machine learning under rules and regulations of PES University, Bengaluru during the period August 2023 – February 2024. It is certified that all corrections / suggestions indicated for internal assessment have been incorporated in the report. The dissertation has been approved as it satisfies the 4th semester academic requirements in respect of project work.

Signature	Signature	Signature	Signature
Sudha B G	**Rohan Rupesh Gurubhaiye**	**Dr. Sandesh B J**	**Dr. B K Keshavan**
Faculty & SM	Senior Data Scientist, GL	Chairperson	Dean of faculty

External Viva

Name of the Examiners	**Signature with dates**
1.________________________	______________________
2.________________________	______________________

DECLARATION

We hereby declare that Project Phase - 2 entitled **“Age Estimation and Gender Detection”** has been carried out by us under the guidance of **Sudha B G**, and submitted in partial fulfillment of the course requirements for the award of the degree of **Master of Technology** in **Data Science and Machine Learning** of **PES University, Bengaluru** during the academic semester August 2023 – December 2023. The matter embodied in this report has not been submitted to any other university or institution for the award of any degree.

PES2PGE21DS264 **Tejonidhi S**

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ABSTRACT

In the realm of computer vision, the accurate estimation of age and recognition of gender from facial images remains a challenging task. This project aims to address this challenge by leveraging the power of Convolutional Neural Networks (CNNs) to predict age and gender from facial images. The UTK dataset, a comprehensive collection of facial images with labeled age and gender information, serves as the foundation for our model training and evaluation. Our CNN model is meticulously designed and trained to capture intricate facial features that correlate with age and gender. Preliminary results indicate a promising accuracy rate, showcasing the potential of CNNs in this domain. The outcomes of this project not only contribute to the advancement of facial recognition technology but also have significant implications for various applications, including personalized advertising, security, and entertainment.

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CHAPTER 1

INTRODUCTION

In today's digital age, the intersection of computer vision and machine learning has led to remarkable advancements in the field of image analysis and understanding. One particularly fascinating application of this technology is the development of systems capable of automatically identifying key demographic attributes of individuals, such as age and gender, from visual data.

The ability to infer age and gender from images or video footage has widespread implications across various domains, including marketing, security, healthcare, and social sciences. From personalized advertising and content recommendation to demographic analysis and public safety, accurate age and gender recognition systems offer valuable insights and opportunities for automation. The ability to automatically infer age [1] and gender [2] from facial images is a key aspect of interpersonal communication and continues to be a prominent field of study for experts in computer vision [3].Gender classification can be done using facial components such as [5],[6],[7] who have mainly used one feature

In our project, we have explored the use of both custom deep learning models and pre-trained architectures, such as VGG16, to develop separate age and gender recognition systems. Each system was trained and evaluated independently using a subset of the UTKFace dataset, consisting of approximately 100 images per age group from 0 to 60 years.For the age recognition component, we employed a custom deep learning model tailored specifically for the task, leveraging techniques such as convolutional neural networks (CNNs) to extract features from facial images and predict age ranges. Meanwhile, for gender recognition, we utilized the pre-trained VGG16 model, fine-tuned on the UTKFace dataset to classify gender accurately. Our approach encompasses a comprehensive pipeline, starting from data collection and preprocessing to model selection, training, and evaluation. We meticulously curated the subset of the UTKFace dataset, ensuring its diversity and quality, and applied advanced techniques in data preprocessing, including face detection and alignment, to standardize the input images. GRA-GAN[4] can be used for to reduce generality in the age estimation.Throughout the development process, we encountered various challenges, including optimizing model hyperparameters, handling class imbalances, and addressing biases inherent in the training data. By conducting separate experiments for age and gender recognition and carefully analyzing the results, we gained insights into the strengths and limitations of each approach. By leveraging both custom deep learning models and pre-trained architectures, we aim to contribute to the ongoing advancement of age and gender recognition technology while adhering to principles of fairness.

CHAPTER 2

PROBLEM STATEMENT

Developing accurate age and gender recognition systems from facial images entails creating models that can predict age ranges and identify genders correctly. Challenges include handling diverse aging appearances and avoiding biases in age predictions, as well as ensuring robustness in gender classification regardless of facial expressions or poses. Obtaining a representative dataset covering various ages, genders, and backgrounds is crucial. Building a comprehensive pipeline for training, validation, and testing, refining models to improve accuracy and fairness, is essential. Ethical considerations are paramount, requiring measures to address privacy, fairness, and bias issues. The goal is to create reliable tools that predict age and gender respectfully and accurately, contributing to technological advancement while upholding ethical standards.

Chapter 3

Literature Review

3.1 Age and Gender Classification using Multiple Convolutional Neural Network.

The methodology proposed in the paper [8] involves a five-phase approach for age and gender classification using facial images. These phases include face detection, background removal, face alignment, the use of multiple Convolutional Neural Networks (CNNs), and a voting system for final classification. Each of the CNNs in the multiple CNN model has a different structure and depth, and they are trained separately on the AGFW dataset. The voting system then combines these individual predictions to arrive at a final result. In terms of results, the paper reports that their multiple CNN model, when combined through a voting system, achieves higher classification accuracy compared to using a single CNN model.

The model was trained and tested on the AGFW dataset, and the authors claim that it outperforms single CNN models in both age and gender classification tasks.

3.2 Gender identification using frontal facial images

The study [9] introduces a novel methodology using Independent Component Analysis (ICA) for gender classification through facial images. The researchers began by normalizing face images to account for variations in geometry and illumination, primarily based on eye location. The normalized images were then processed to represent them in a lower- dimensional space using ICA. This representation was further used for gender identification, employing various classification algorithms. The paper's experiments utilized the FERET facial dataset, which consists of frontal shots of individuals. Through their methodology, the researchers achieved a classification accuracy of up to 95.67% using Support Vector Machine (SVM) in the ICA space. This approach, as presented, offers a promising direction for gender classification using facial images, potentially paving the way for more advanced applications in biometrics and human-computer interaction. Independent Component Analysis for facial images representation has been used[10].

3.3 Automatic age classification with LBP

The research [11] focuses on the significance of estimating age from facial images, particularly in security systems design. The paper employs local binary patterns (LBP) to classify age from facial images. LBPs are fundamental properties of local image texture, and their occurrence histogram serves as an effective texture feature for face description. The study classifies FERET images based on their ages at 10-year intervals. Faces are divided into small regions, from which LBP histograms are extracted and combined into a feature vector, serving as an efficient face descriptor. For every new face introduced to the system, spatial LBP histograms are generated and used to classify the image into one of the age classes. During the classification phase, various classifiers like minimum distance, nearest neighbor, and k-nearest neighbor are employed. Experimental results indicate an 80% system performance for age estimation using spatial LBP histograms. The study suggests that finding optimal region weights could further enhance system performance.

3.4 Automatic age estimation based on facial aging patterns

The research [12] delves deep into an innovative approach that underscores the interplay between universal aging patterns and individual-specific aging trajectories. FG-NET Aging database[13] has been used, acknowledging the unique nuances of how faces age, the authors emphasize the dual importance of shared aging characteristics across individuals and the distinct aging patterns unique to each person. The proposed methodology operates in a cyclical manner: initially, any gaps or missing elements in an individual's aging pattern are inferred using the prevailing model of global aging patterns. This is followed by refining and updating the global model based on the newly inferred individual aging patterns. Such a method ensures a balanced consideration of both the shared and unique features of aging, iteratively leveraging each to refine the overall aging subspace.

3.5 Gender classification based on fusion of facial components features. The research [14] delves into the realm of image processing, particularly focusing on gender classification using facial components. The study emphasizes the significance of facial components in conveying a plethora of information, which can be harnessed for various applications. The paper introduces a gender classification methodology that fuses facial components like eyes, nose, mouth, forehead, and cheeks. This fusion aims to counteract challenges like occlusion that might obstruct the camera's view of a facial image and to enhance the classification rate of features with lower accuracy. The research employed an artificial neural network with back propagation for classification. The findings revealed that fusion could enhance the accuracy rates of components with lower classification. For instance, the mouth, which individually had an accuracy rate of 75%, achieved an accuracy of 87% when fused with the nose's feature vector, which had a standalone classification rate of 90%. This fusion approach proves beneficial, especially when a significant portion of a component with higher classification accuracy is obscured.

CHAPTER 4

SYSTEM REQUIREMENTS SPECIFICATION

4.1 Product Perspective

Our age and gender recognition project aims to deliver a robust and scalable solution that meets the needs of diverse stakeholders. This involves defining clear requirements, prioritizing features based on user feedback, and ensuring compatibility with various platforms and applications. By focusing on usability, performance, and reliability, we strive to create a product that offers value to end-users while aligning with business objectives and market demands. Additionally, we emphasize continuous improvement through iterative development cycles, incorporating user insights and technological advancements to enhance the product's functionality and usability over time.

4.1.1 Product Features

Our age and gender recognition project prioritizes functionality, usability, and versatility. This includes core features such as accurate age range prediction and gender classification from facial images, supported by robust model architectures and efficient algorithms. Our solution incorporates two models: a custom deep learning model tailored specifically for age prediction and another leveraging the VGG16 pre-trained architecture for gender classification. These models are trained on a subset of the UTKFace dataset, ensuring diverse representation and reliable performance across various demographic groups. Additionally, we aim to incorporate features for real-time processing, cross-platform compatibility, and seamless integration with existing systems. By focusing on these key features, we ensure that our solution meets the needs of users across various applications and environments, providing value and utility in diverse scenarios.

4.1.2 User Classes and Characteristics

The target audience and frequent users of our age and gender recognition system include researchers, developers, software engineers, data scientists, businesses, enterprises, government agencies, law enforcement, and end users. These users vary in technical expertise, domain knowledge, and specific use case requirements, highlighting the importance of designing a system that meets usability, performance, and ethical standards across diverse scenarios.

4.1.3 Operating Environment

Our age and gender recognition system currently operates within the Jupyter Notebook environment, enabling interactive development and testing of machine learning models. While initially deployed in Jupyter Notebook, the system is designed for flexible deployment across desktop, server, cloud, and edge computing environments.

4.1.4 General Constraints, Assumptions, and Dependencies

Our age and gender recognition system operates under the following conditions:

- **Data Availability**: It relies on diverse and quality facial image data for training and testing, which may pose constraints if the dataset lacks diversity or contains biases.
- **Computational Resources:** The system's performance is dependent on the availability of computational resources like CPUs, GPUs, and memory for model training and inference.
- **Model Complexity:** Effectiveness hinges on the complexity and accuracy of age and gender recognition models chosen or built, with assumptions made about their suitability for the task.
- **Ethical and Legal Considerations:** Operation adheres to ethical guidelines and legal regulations, including privacy concerns, data protection laws, and biases in algorithmic decision-making.
- **Integration Dependencies:** Successful integration into existing applications or platforms relies on factors such as compatibility with programming languages, frameworks, and APIs.

- **Maintenance and Support:** Long-term viability is contingent on ongoing maintenance, updates, and technical support to address software bugs, optimize performance, and meet evolving user requirements.

4.2 Functional Requirement

Our age and gender recognition system is expected to:

- Accept facial images for age and gender prediction.
- Accurately predict age ranges and classify gender.
- Support model training, evaluation, and real-time processing.
- Ensure compatibility across various platforms.
- Facilitate integration into existing applications.
- Optionally provide a user interface for interaction and visualization.

4.3 External Interface Requirements

4.3.1 Hardware Requirements

Our age and gender recognition system needs the following:

- **CPU:** A multi-core processor with sufficient processing power for model training and inference. A modern CPU such as Intel Core i5 or AMD Ryzen 5 is recommended. **GPU (Optional):** A dedicated graphics processing unit (GPU) can significantly accelerate deep learning tasks, especially model training. NVIDIA GPUs such as GeForce GTX or RTX series are commonly used for this purpose.
- **Memory (RAM):** Adequate RAM is essential for handling large datasets and model parameters efficiently. A minimum of 8GB RAM is recommended for basic usage, while 16GB or more is preferable for intensive tasks.
- **Storage:** Sufficient storage space is required for storing datasets, model files, and related resources. An SSD (Solid State Drive) is preferable for faster data access and model loading times.

- **Operating System:** The system should be compatible with popular operating systems such as Windows, Linux, or macOS, depending on user preferences and software requirements.
- **Other:** Additional hardware components such as a webcam or camera may be required for capturing facial images in real-time applications.

4.3.2 Software Requirements

- **Operating System:** Compatibility with major operating systems like Windows, Linux, or macOS.
- **Programming Languages:** Support for languages such as Python for development and integration**.**
- **Frameworks and Libraries:** Utilization of deep learning frameworks like TensorFlow or PyTorch for model development.
- **Development Environment:** Access to development environments like Jupyter Notebook for prototyping and experimentation.
- **Version Control:** Integration with version control systems like Git for collaborative development and code management.
- **Dependency Management:** Utilization of package managers such as pip or conda to manage software dependencies.
- **Other Tools:** Integration with data processing tools, visualization libraries, and performance monitoring utilities as needed for system functionality and optimization.

4.4 Non-Functional Requirements

Non-functional requirements specify the standards to judge the operation of the system. Unlike functional requirements, which specify the behavior of the system, Non-Functional requirements establish system qualities. They may include timing constraints, constraints on the system such as capabilities of the IO devices, and memory occupancy. They usually apply to the system as a whole.

4.4.1 Performance Requirements

- Achieve low-latency response times and high throughput for real-time or near real-time processing.
- Ensure high accuracy, scalability, resource utilization, reliability, and robustness.
- Incorporate security measures and comply with ethical and regulatory standards.

4.4.2 Safety Requirements

- **Data Privacy:** Protect user privacy through robust data anonymization and encryption.
- **Fairness and Bias Mitigation:** Mitigate biases in algorithms to ensure fair treatment.
- **Adverse Event Handling:** Handle system failures or inaccuracies to minimize harm.
- **Ethical Use:** Adhere to ethical guidelines and regulations in system deployment.
- **User Consent:** Obtain explicit user consent for data collection and processing.

4.4.3 Security Requirements

- Encrypt sensitive data for confidentiality.
- Enforce strict access controls.
- Use secure communication protocols.
- Protect against common security threats.
- Manage vulnerabilities effectively.
- Implement robust logging and monitoring.
- Define data retention and disposal policies.
- Ensure compliance with relevant security standards and regulations.

CHAPTER 5

SYSTEM DESIGN

5.1 Design Details

5.1.1 Novelty

The novelty of our age and gender recognition project lies in several key areas. Firstly, we're exploring custom model architectures specifically tailored for these tasks, integrating innovative features and attention mechanisms. Secondly, we're investigating multimodal fusion techniques to combine visual data with contextual cues for enhanced accuracy. Additionally, we're developing ethical frameworks and bias mitigation techniques to ensure fairness, transparency, and privacy in our models. Furthermore, we're focusing on real-time recognition and cross-cultural validation to understand and address demographic influences. By innovating in these areas, our project aims to advance the field of age and gender recognition while contributing novel insights and solutions.

5.1.2 Innovativeness

The innovativeness of our age and gender recognition project lies in several key aspects. Firstly, we're pioneering the development of custom model architectures specifically tailored to these tasks, integrating innovative features and attention mechanisms to improve performance. Secondly, we're exploring novel approaches to multimodal fusion, combining visual data with contextual cues to enhance accuracy and robustness. Additionally, we're leading the way in addressing ethical concerns by developing frameworks and techniques to mitigate biases, ensure fairness, and protect privacy. Moreover, our focus on real-time recognition and cross-cultural validation sets us apart, allowing us to understand and adapt to diverse demographic influences. By pushing the boundaries of current research and technology in these areas, our project aims to make significant contributions to the field of age and gender recognition.

5.1.3 Interoperability

The system will perform irrespective of the operating system. However, since we are dealing with facial data, it would require the system to have a GPU.

5.1.4 Performance

The proposed system will be built to handle large amounts of facial data.

5.1.5 Security

The system should ensure zero vulnerabilities in the form of bugs or faults which might cause the system to fail or crash.

5.1.6 Reliability

With a significant dataset comprising 6878 images, the system has demonstrated reliability with minimal false positives. The nuanced precision of the model is reflected in its predictive outcomes, with the majority of faces correctly identified with correct age and gender.

5.1.7 Maintainability

Our age and gender recognition project emphasizes a modular design, comprehensive documentation, and adherence to version control practices. These measures streamline maintenance and future updates. By upholding coding standards, implementing automated testing, and fostering a collaborative development environment, we ensure the adaptability and longevity of our system, accommodating evolving needs and advancements in the field.

5.1.8 Portability

Our age and gender recognition project holds high promise with innovative model architectures, advanced multimodal fusion, and a robust ethical framework, poised to address biases, enable real-time recognition, and advance the field ethically and practically.

5.1.9 Reusability

Regarding reusability, our age and gender recognition project is designed with modularity and versatility in mind. This ensures that components such as model architectures, data preprocessing methods, and evaluation metrics can be easily adapted and reused in other projects or contexts.
By promoting code reuse, documentation clarity, and standardization of interfaces, we facilitatthe seamless integration of our work into future endeavors, maximizing efficiency and reducing redundancy in development efforts.

5.1.10 Application compatibility

In terms of application compatibility, our age and gender recognition project is developed to seamlessly integrate with a variety of applications and platforms. This includes ensuring compatibility with popular operating systems, programming languages, and development frameworks commonly used in the industry. By adhering to industry standards and leveraging cross-platform technologies where applicable, we ensure that our solution can be easily deployed and integrated into diverse applications across different domains and environments. This enhances its versatility and usability, enabling broader adoption and impact.

5.1.11 Resource utilisation

Our age and gender recognition project optimizes computational efficiency by employing lightweight algorithms and scalable model architectures. This ensures effective use of available hardware resources while maintaining high performance. Through techniques such as parallel processing and memory management, we minimize waste and enhance scalability across diverse computing environments.

CHAPTER 6

PROPOSED METHODOLOGY

6.1 CUSTOM CNN MODEL

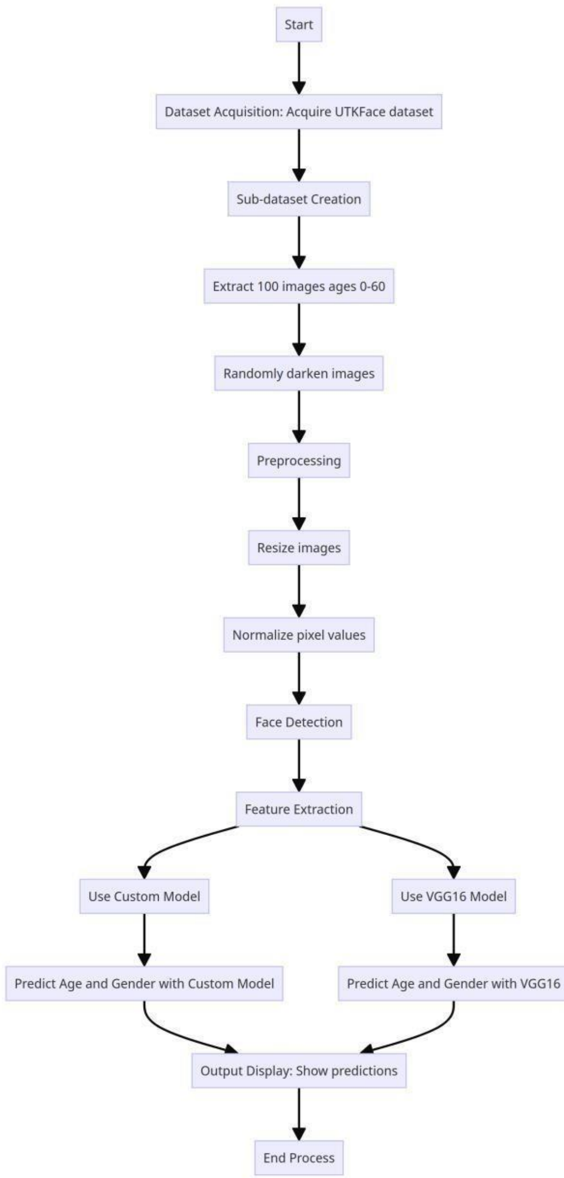

Fig 6.1 Proposed Methodology

6.1.1 Training Phase

Our age and gender recognition system utilizes the UTKFace dataset for model training. The training process involves the following steps:

- **Dataset Acquisition:** We procure the UTKFace dataset, a large-scale dataset containing facial images annotated with age, gender, and ethnicity labels.
- **Sub-dataset Creation:** To ensure balanced representation across age categories, we create a specialized subset of the dataset containing 100 images for each age range from 0 to 60 years old. This sub-dataset enables our model to learn age-related features effectively.
- **Data Preprocessing:** Before training, we preprocess the sub-dataset by resizing images, normalizing pixel values, and augmenting the dataset through techniques such as rotation, flipping, and cropping. Additionally, we apply a darkening transformation to simulate variations in lighting conditions commonly encountered in real-world scenarios.
- **Model Selection:** We choose appropriate model architectures for age prediction and gender classification, considering factors such as model complexity and performance. This includes custom deep learning models and pre-trained architectures like VGG16.
- **Training Configuration:** We configure training parameters such as learning rate, batch size, and optimization algorithm to optimize model performance.
- **Model Training:** The selected models are trained using the preprocessed subdataset, iteratively adjusting model parameters to minimize prediction errors and optimize performance.
- **Validation and Hyperparameter Tuning:** We validate model performance on a separate validation dataset and fine-tune hyperparameters to improve generalization and prevent overfitting.
- **Model Evaluation:** Trained models are evaluated on a held-out test dataset to assess performance metrics such as accuracy and precision.
- **Model Saving:** Finally, we save trained models and associated weights for future deployment and inference.

6.1.2 Testing Phase

- **Dataset Preparation:** We prepare a testing dataset comprising facial images not used during training or validation to ensure unbiased evaluation of model performance.
- **Data Preprocessing:** Similar to the training phase, we preprocess the testing dataset by resizing images, normalizing pixel values, and applying any necessary transformations to ensure consistency with the training data**.**
- **Model Loading:** We load the trained models saved during the training phase, including both the age prediction and gender classification models.
- **Inference:** We perform inference on the testing dataset using the trained models, obtaining predictions for age ranges and gender classifications for each facial image.
- **Performance Evaluation:** We evaluate the performance of the system using appropriate metrics such as accuracy, precision for age prediction and gender classification tasks. This allows us to assess the effectiveness and generalization capability of the trained model**s.**
- **Analysis and Interpretation:** We analyze the evaluation results to identify any potential areas for improvement or optimization. This may involve examining misclassified samples, investigating model biases, or comparing performance across different demographic groups. Age distribution graph of our dataset till the age of 60

CHAPTER 7

IMPLEMENTATION & PSEUDOCODE

7.1 Implementation of Custom CNN Model

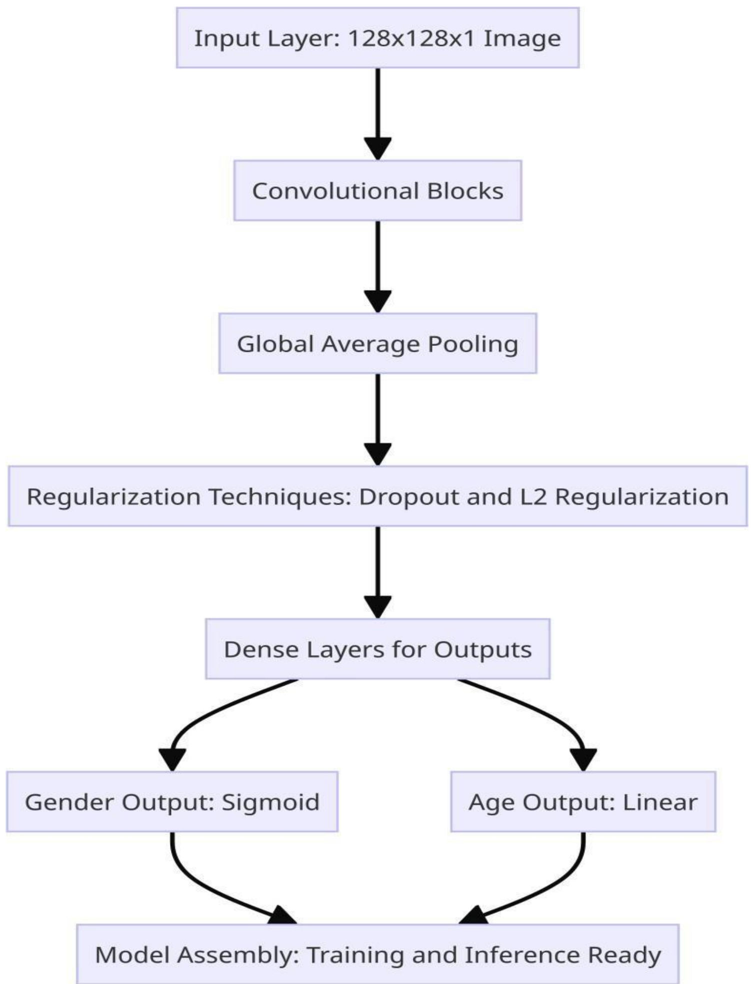

Fig 7.1 CNN Model Layers

- **Input Layer:**

  The model expects an input shape of (128, 128, 1), which indicates a single- channel image (likely grayscale) of size 128x128.

- **First Convolutional Block:**
  - **Convolutional Layer:** Uses 32 filters of size (3, 3).
  - **Activation Layer:** Implements the Rectified Linear Unit (ReLU) activation function.
  - **Pooling Layer:** Applies max pooling with a pool size of (2, 2).
- **Second Convolutional Block:**
  - **Convolutional Layer:** Uses 64 filters of size (3, 3).
  - **Activation Layer:** Implements the Rectified Linear Unit (ReLU) activation function.
  - **Pooling Layer:** Applies max pooling with a pool size of (2, 2).
- **Third Convolutional Block:**
  - **Convolutional Layer:** Uses 128 filters of size (3, 3).
  - **Activation Layer:** Implements the Rectified Linear Unit (ReLU) activation function.
  - **Pooling Layer:** Applies max pooling with a pool size of (2, 2).
- **Fourth Convolutional Block:**
  - **Convolutional Layer:** Uses 256 filters of size (3, 3).
  - **Activation Layer:** Implements the Rectified Linear Unit (ReLU) activation function.
  - **Pooling Layer:** Applies max pooling with a pool size of (2, 2).

- **Fifth Convolutional Block:**
  - **Convolutional Layer:** Uses 512 filters of size (3, 3).
  - **Activation Layer:** Implements the Rectified Linear Unit (ReLU) activation function.
  - **Pooling Layer:** Applies max pooling with a pool size of (2, 2).
- **Sixth Convolutional Block:**
  - **Convolutional Layer:** Uses 1024 filters of size (3, 3) with padding same.
  - **Activation Layer:** Implements the Rectified Linear Unit (ReLU) activation function.
  - **Pooling Layer:** Applies max pooling with a pool size of (2, 2).
- **Gender Output:**
  - **Dense Layer:** 256 units with ReLU activation function.
  - **Dropout Layer:** Applies dropout with a rate of 0.5.
  - **Output Layer:** Single unit with Sigmoid activation function, named 'gender_out'.
- **Age Output:**
  - **Dense Layer:** 256 units with ReLU activation function.
  - **Dropout Layer:** Applies dropout with a rate of 0.5.
  - **Output Layer:** Single unit with linear activation function, named 'age_out'.

This architecture is typical of CNNs used for image classification tasks. The convolutional layers are responsible for feature extraction, while the fully connected layers at the end are responsible for classification. The use of pooling layers helps in reducing the spatial dimensions, and the dropout layer aids in preventing overfitting during training.

7.1.1 Model Compilation Parameters

1. Loss Function:

- **Binary Crossentropy:** Binary Cross-Entropy, often abbreviated as BCE or binary log loss, is a commonly used loss function in machine learning and deep learning,

  particularly for binary classification tasks. It is used to measure dissimilarity between the predicted probability distribution and the actual binary labels (0 or 1) of a dataset. Binary Cross-Entropy is also known as log loss or logistic loss.

$$H_p(q) = -\frac{1}{N}\sum_{i=1}^{N} y_i \cdot log(p(y_i)) + (1 - y_i) \cdot log(1 - p(y_i))$$

Fig 7.2 Binary Cross Entropy Function

Where,

N – is the total number of samples or data points

yi – is the actual label for the ith sample (0 or 1)

yi – is the predicted probability that the ith sample belongs to class 1 (the probability of the positive class)

2. Optimizer:

- **Adam**: The Adam optimizer is an adaptive learning rate optimization algorithm. It combines the best properties of the AdaGrad and RMSProp optimization algorithms. Adam computes adaptive learning rates for each parameter, making it suitable for training deep neural networks. It's known for its efficiency and low memory requirements.

3. Metrics:

- **Accuracy**: Accuracy is a metric that calculates the ratio of correctly predicted instances to the total instances in the dataset. It provides a measure of the model's performance in terms of how many predictions it got right. It's commonly used for classification tasks.

By compiling the model with these parameters, we're setting it up to minimize the categorical cross-entropy loss using the Adam optimizer during training. Additionally, the model's performance will be evaluated using accuracy as it’s metric.

- **MAE-** The Mean Absolute Error (MAE), also known as L1 Loss, is a loss function used in machine learning, particularly for regression tasks. It calculates the average absolute differences between the predicted values from a machine learning model and the actual target values.

$$MAE = \frac{1}{N} \sum_{i=1}^{N} |Y_i - \hat{Y}_i|$$

Fig 7.3 MAE Function

4. CallBacks:

- **ReduceLROnPlateau:** Reduces the learning rate when the validation loss has stopped improving after a certain number of epochs (patience).
- **Early Stopping:** Stops the training process early if the validation loss stops improving for a certain number of epochs (patience). It also restores the best weights of the model.
- **Model Checkpoint:** Saves the model weights whenever the validation loss decreases, ensuring that the best model is saved.

7.2 Implementation of Pre-Trained VGG16 Model

- **Base Model:** VGG16 with pre-trained ImageNet weights, excluding the top classification layers.
- **Input Shape:** (220, 220, 3) - Input images are expected to be 220x220 pixels with 3 color channels (RGB).
- **Layer Freezing:**
  - The first 15 layers of the VGG16 base model are frozen (non-trainable).
    - Layers after index 15 are set to trainable,allowing them to be updated during

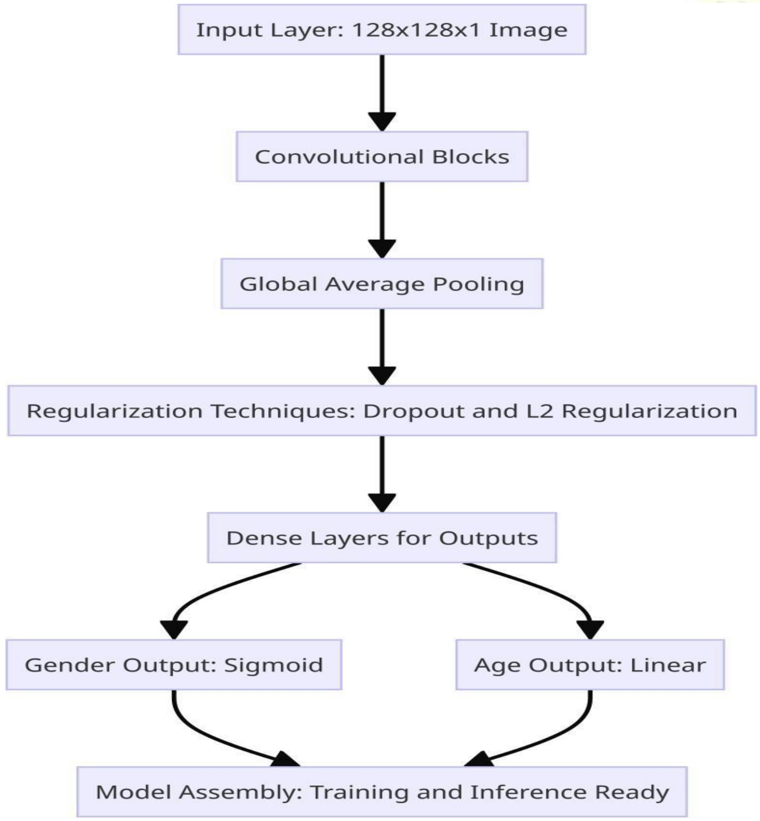

Fig 7.4 Model Layers of VGG16

- **Detailed Architecture:**
  - ➢ **Input Layer:** Shape: (220, 220, 3)
  - ➢ **VGG16 Base Model:** Pre-trained on ImageNet, Top classification layers excluded.
  - ➢ **Flatten Layer:** Flattens the output of the VGG16 base.
  - ➢ **Dense Layers (Age Prediction):**
    - **Dense 1:** 256 units, ReLU activation.
    - **Dense 2:** 256 units, ReLU activation.
    - **Output Layer:** Single neuron with linear activation for age prediction.
  - ➢ **Dense Layers (Gender Prediction):**
    - **Dense 1:** 256 units, ReLU activation.

- ○ **Dense 2:** 256 units, ReLU activation.

➤ **Output Layer:** Single neuron with sigmoid activation for gender prediction.

Training Configuration:

- **Loss Function:**
  - ○ **Age Prediction:** Mean Squared Error (MSE) - Regression task.
  - ○ **Gender Prediction:** Binary Crossentropy - Binary classification task.
  - ○ **Optimization Algorithm:** Adam
- **Learning Rate:** Metrics: 0.0001
- **Model Compilation:** Compile the model with appropriate loss functions, optimizers, and metrics for each output.
- **CallBacks:**
  - ○ **ReduceLROnPlateau:** Reduces the learning rate when the validation loss has stopped improving after a certain number of epochs (patience).
  - ○ **Early Stopping:** Stops the training process early if the validation loss stops improving for a certain number of epochs (patience). It also restores the best weights of the model.
  - ○ **Model Checkpoint:** Saves the model weights whenever the validation loss.

Sample Image from the dataset chosen

Fig 7.5 Sample image from the dataset chosen [15]

CHAPTER 8

RESULTS AND DISCUSSION

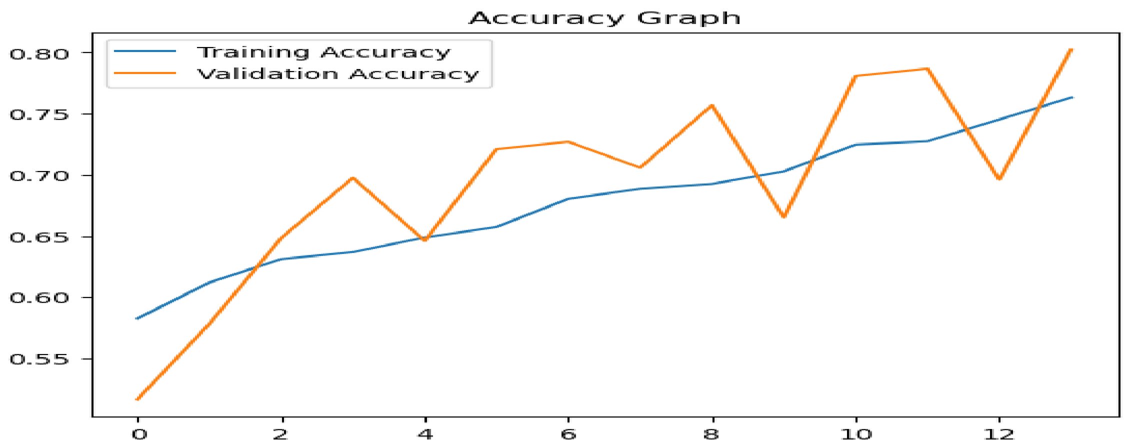

Fig 8.1 Accuracy Graph of Custom Model for Gender

The Gender accuracy graph**(Fig 8.1)** portrays the behavior of a model's training and validation loss over a series of epochs. The blue line, representing training accuracy, and the orange line, for validation accuracy. Validation accuracy, denoted by the orange line, has a slightly more tumultuous path. Initially falling short of training accuracy, it swiftly climbs and at times outpaces the training performance. This quick surpassing of the training accuracy may reflect an effective capture of generalizable patterns rather than mere memorization of the training data.

However, the fluctuations in validation accuracy are more pronounced than those in training accuracy. This volatility could be a sign that the model's adaptability to new data is not entirely stable, suggesting the need for further refinement to enhance model generalization.

As we move through successive epochs, we witness the training and validation accuracies converging. This convergence is a positive indication that the model is not overfitting significantly. The congruence between the two metrics suggests a balance between learning from the training data and maintaining flexibility to adapt to new, unseen data.

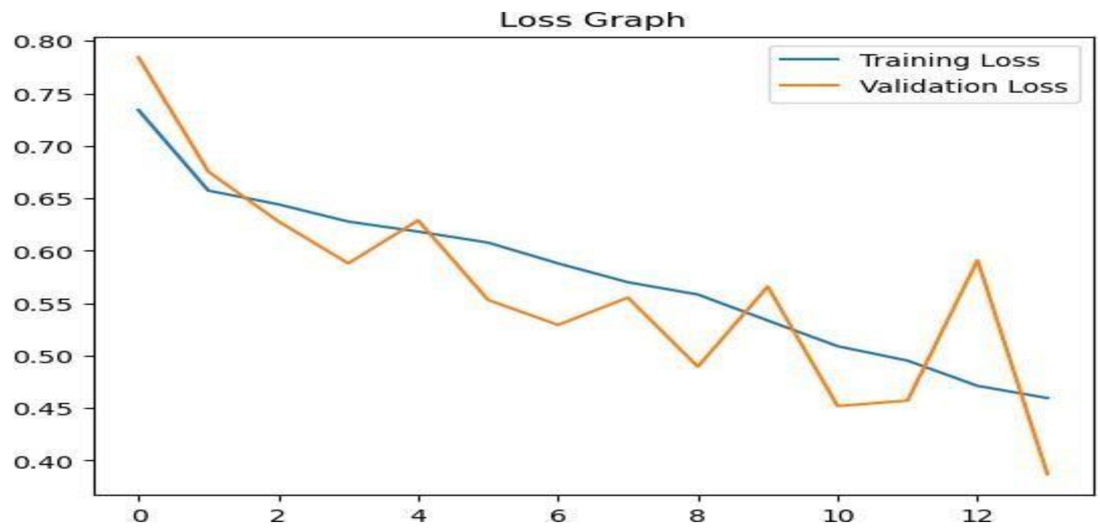

Fig 8.2 Loss Graph of Age for Custom Model

The Gender loss graph**(Fig8.2)** portrays the behavior of a model’s training and validation loss over a series of epochs. Loss is a numerical value indicating how well the model's predictions match the actual data, with a lower loss corresponding to better performance.

The training loss starts higher and exhibits a steep decline in the initial epochs. This rapid decrease is typical of the early stages of training, where the model rapidly learns from the training data.

The validation loss also shows a sharp decrease, closely following the training loss, which suggests that improvements in the model are generalizing well to unseen data. The overall downward trend of both the training and validation loss is promising, indicating ongoing learning and improvement. By the end of the graphed epochs, training and validation loss seem to be converging, which is a good sign. Convergence at a low loss value would indicate a model that generalizes well.

The graph ends with the validation loss slightly higher than the training loss. This ending point implies that the model might benefit from additional training epochs, as there’s no strong sign of overfitting, where we would see the validation loss increasing while the training loss decreases.

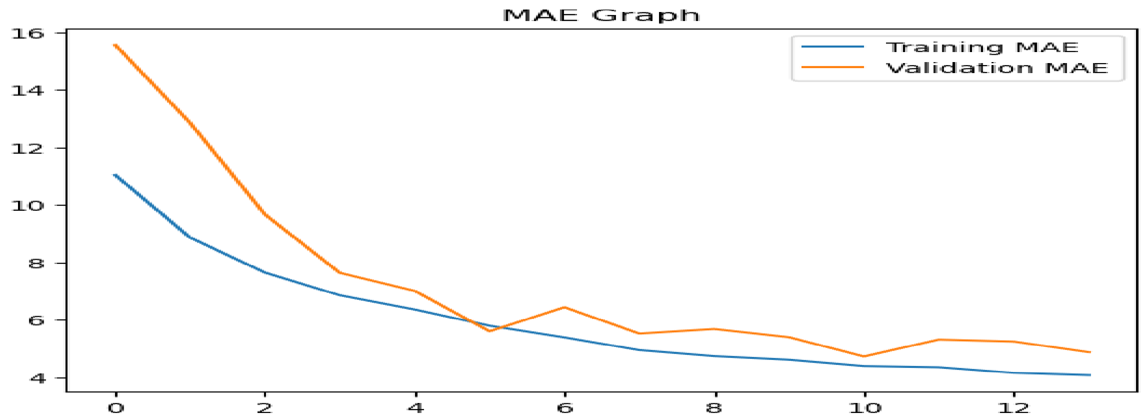

Fig 8.3 Age MAE Graph of Custom CNN Model

The graph depicting the Mean Absolute Error (MAE) **(Fig 8.3)** for age prediction over training epochs offers valuable insights into your model's performance. The rapid initial decrease in both training and validation MAE suggests that the model is effectively learning from the data. The subsequent plateauing of the validation MAE, particularly after the sixth epoch, indicates the model is nearing its learning capacity given its current architecture and the data provided. The close proximity of the training and validation MAE in later epochs suggests good generalization, with no significant overfitting observed. The model seems to achieve a reasonably low MAE, suggesting it predicts age with an acceptable error margin. Improvements could potentially be realized through hyperparameter tuning, implementing early stopping, or augmenting the dataset to help the model generalize better. MAE around 4 years in the later epochs is indicative of a robust model.

So overall it can be said that the custom CNN model achieved a Gender accuracy of around 86% and Age MAE of around 4 years for dataset containing around 13000 images.

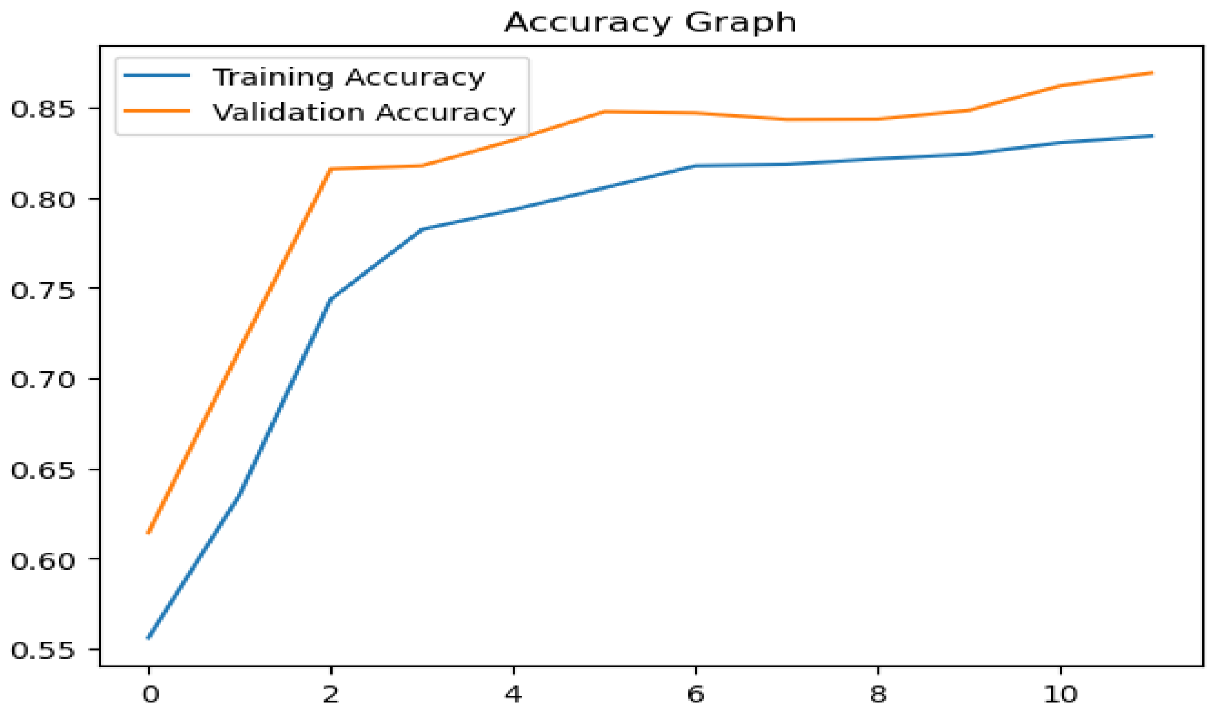

Fig 8.4 Gender Accuracy Graph of VGG16 Model

The accuracy graph reflects the model's performance on gender classification over training 12 epochs. Initially, both training and validation accuracy swiftly increase, suggesting the model quickly learned relevant features from the data. As the epochs progress, training accuracy continues to rise, albeit at a slower pace, reaching a plateau near the end, which implies a saturation point where the model has nearly maximized its learning from the training data.

Validation accuracy also improves rapidly at first but then begins to plateau after the fourth epoch. Notably, the validation accuracy slightly overtakes the training accuracy at around the eighth epoch, which is unusual and could indicate exceptionally good generalization, or that the validation set may contain some easier examples than the training set.

The graph converges to a narrow margin, suggesting the model is generalizing well without overfitting, as evidenced by the close tracking between the training and validation accuracy. A consistent improvement in validation accuracy over training accuracy could also hint at a conservative learning process that could benefit from further optimization.

In summary, the model displays robust learning capability and generalization, with both accuracies plateauing towards the end of the observed epochs, indicating that additional gains from further training may be limited without modifications to the model or training process.

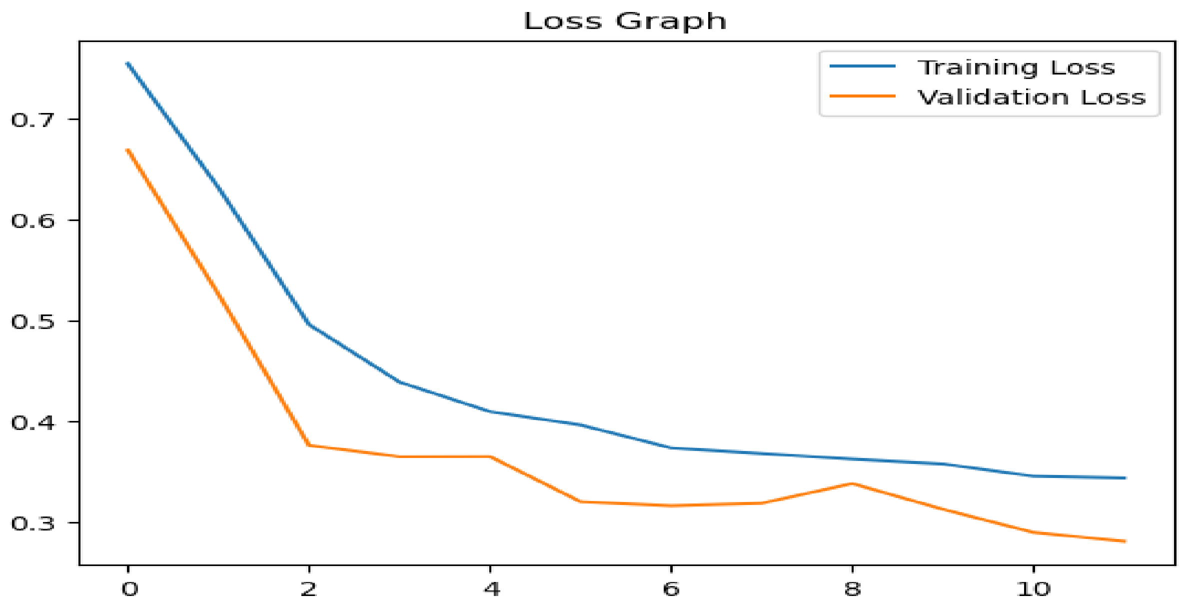

Fig 8.5 Gender Loss Graph of VGG16 Model

The loss graph for our model training depicts a steep initial decrease in both training and validation loss with 12 epochs, signifying rapid learning. As training progresses, both losses exhibit a converging trend, indicative of the model's ability to generalize to new data. The absence of significant divergence between the training and validation lines throughout the epochs suggests that the model is not overfitting and is maintaining a balance between learning from the training data and generalizing to the validation data. The graph shows the losses plateauing after the initial drop, hinting that the model may be nearing its optimal performance with the given architecture. This plateau implies that additional training is unlikely to result in substantial improvements and could potentially lead to overfitting. Early stopping or exploring advanced model architectures or tuning strategies may be necessary to enhance the model's performance further. The overall loss trends confirm a well-fitting model that has effectively learned from the training phase and is expected to perform reliably on similar unseen data.

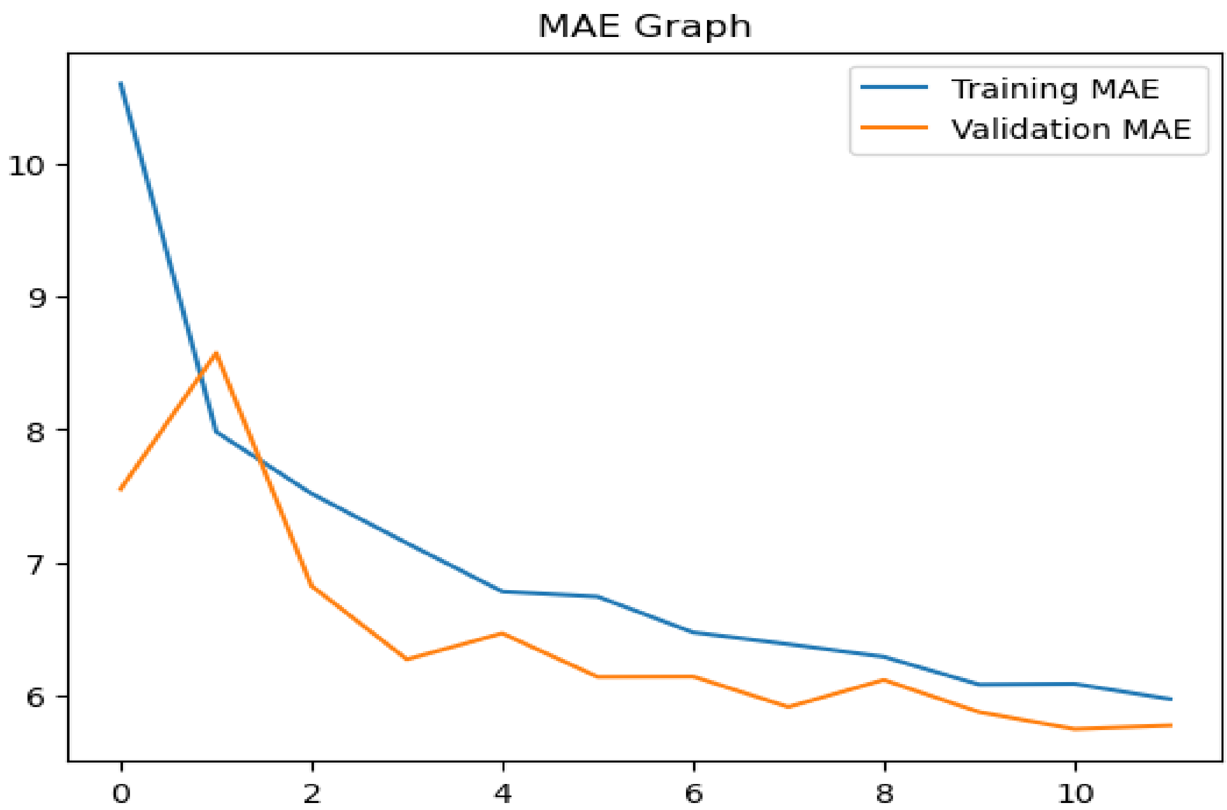

Fig 8.6 Age MAE Graph for VGG16 Model

The Mean Absolute Error (MAE) trends for a deep learning model over training epochs were analyzed to evaluate the accuracy in predicting ages. The MAE metric was chosen for its clarity in representing average prediction errors with epochs 12.

Upon commencement of training, the model's MAE sharply declined, indicating rapid learning from the training data. Subsequently, the training MAE demonstrated a consistent decrease over epochs, confirming the model's improving capability in age prediction. Notably, the validation MAE initially peaked, suggesting early model volatility when applied to unseen data. This peak was followed by a downward trend, mirroring the training MAE, and indicating that the model was beginning to generalize well beyond the training dataset.

The graph reveals the training and validation MAE converging, a sign of the model's stabilized performance and reduced overfitting risk. The convergence, along with a plateauing effect observed in later epochs, suggests that further training would yield diminishing improvements and could be a signal to employ early stopping to prevent overfitting and unnecessary computation. In conclusion, the depicted MAE progression indicates a successful training phase with the model's predictive accuracy on age improving over time. The initial volatility in validation MAE points to potential areas for refinement, such as implementing regularization or modifying hyperparameters to enhance model generalization.

Fig 8.7 Real Time result of Custom Model

From the above figure we can see that the original age is 35 and gender is female, our model prediction also came close when it comes to age predicting age as 33 and the correct gender as Female.

Fig 8.8 Real Time result of VGG16 model

From the above image we can see that our VGG16 model was able to guess the gender correctly i.e Female, the age was offset by 6 years which is appropriate as the MAE is 6 for the VGG16 model.

Fig 8.9 Estimation of Age and Gender Of Teenager in custom model

From the above figure we can see that the original age for a young 11 and gender is female, our model prediction also came close when it comes to age predicting age as 12 and the correct gender as Female

```
1/1 [==============================] - 0s 301ms/step
Predicted Gender: Female
Predicted Age: 0
```

Fig 8.9 Misclassification of Gender in VGG16 Model

From the above figure we can see that the original age for a young 1 and gender is female, our model prediction also came close when it comes to age predicting age as 0 and misclassified the gender as Female instead of Male.

In conclusion the custom CNN model's Gender Accuracy is around 85% and the MAE is 5 years, w.r.t VGG16 model the Gender Accuracy is around 83% and the MAE is around 6 years.

Conclusion

After training two distinct models for gender classification and age estimation, we find that both demonstrate progressive learning capabilities, yet they exhibit different patterns and final outcomes. The first model starts with a relatively high loss but makes significant strides in both the gender and age prediction tasks as the epochs advance. There's a marked reduction in loss, with an ultimate improvement in the gender classification accuracy up to 85.51% and a reduction in mean absolute error for age estimation. Despite some fluctuations in validation loss, which may signal moments of overfitting or sensitivity to the validation data, the model achieves a commendable balance between its dual objectives. In contrast, the second model, based on the VGG16 architecture, shows a more consistent and stable improvement over the epochs. The loss decreases are steady, and the model reaches higher accuracy for gender classification at 83.41%. Notably, this model begins with a lower initial loss compared to the first, suggesting that the VGG16 architecture might be better at capturing features relevant to the tasks from the onset of training.

In conclusion, while both models demonstrate effective learning, the VGG16-based model appears to offer a more stable and consistent performance, particularly in gender classification. However, the first model shows considerable potential, especially in its robust learning rate for the gender classification task. The choice between models would likely depend on specific use- case requirements: for applications needing stability and consistency, the custom model might be preferable, whereas for contexts where a balance between gender and age prediction is vital, the custom model could be more suitable. For age estimation, the downward trend in MAE for both models is encouraging, yet the observed volatility underscores the complexity of the task and the necessity for additional strategies, such as enhanced regularization, to improve prediction stability. Future work will involve refining the models through advanced techniques, including hyperparameter tuning and exploring alternative architectures. The combined results fortify the potential of using convolutional neural networks for these tasks and pave the way for more nuanced models that are robust against a wider array of real-world data.

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