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CAPSTONE PROJECT REPORT
(Project Term January-April 2023)

GENDER CLASSIFICATION USING FACIAL IMAGES

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School of Computer Science and Engineering

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DECLARATION

We hereby declare that the project work entitled 'Gender classification from facial image' is an authentic record of our own work carried out as requirements of Capstone Project for the award of B. Tech degree in Computer Science and Engineering from Lovely Professional University, Phagwara, under the guidance of Ms. Harjeet Kaur, during January to April 2023. All the information furnished in this capstone project report is based on our own intensive work and is genuine.

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CERTIFICATE

This is to certify that the declaration statement made by this group of students is correct to the best of my knowledge and belief. They have completed this Capstone Project under my guidance and supervision. The present work is the result of their original investigation, effort, and study. No part of the work has ever been submitted for any otherdegree at any University. The Capstone Project is fit for the submission and partial fulfilment of the conditions for the award of B. Tech degree in Computer Science and Engineering from Lovely Professional University, Phagwara.

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1.INTRODUCTION

Gender categorization from face photographs is a difficult topic in computer vision and pattern recognition. The capacity to automatically determine an individual's gender based ona face photograph has multiple uses in fields such as marketing, surveillance, and human- computer interaction. Because of the differences in face appearance induced by changes in lighting, position, expression, and occlusion, gender detection is a crucial and difficult undertaking. Significant progress has been achieved in the development of algorithms for gender classification from face photos in recent years. The extraction of significant information from facial photos is often followed by categorization using machine learning approaches in these algorithms.

The human face is a complicated entity with several traits that may be used to classify gender. The physical variations between male and female faces establish gender. The size and form of the jaw, nose, forehead, brows, and eyes are examples of these variances. Machine learning algorithms may be trained to recognise gender from face photos using the variance in these characteristics.

The extraction of facial features is a critical stage in gender categorization. face landmarks, texture, and form are the most often utilised face traits for gender categorization. Facial landmarks are particular spots on the face that may be used to find and characterise facial characteristics, such as the corners of the eyes and mouth. The patterns of skin texture on the face that can be utilised to distinguish between male and female faces are referred to as facial texture. The characteristics of the face, such as the jawline and cheekbones, can be utilised to differentiate between male and female faces.

Gender categorization from face photos has been accomplished using a variety of machine learning approaches. Support vector machines (SVMs), decision trees, k-nearest neighbour (KNN) methods, artificial neural networks (ANNs), and convolutional neural networks (CNNs) are just a few examples. SVMs are one of the most widely utilised gender categorization algorithms. SVMs function by locating a hyperplane based on the feature vectors of the male and female faces. Another prominent approach is decision trees, which function by recursively partitioning the feature space until a choice is obtained. KNN methods categorise a test sample by locating its nearest neighbours in the feature space and

using the labels of those neighbours to classify the sample. ANNs are biologically inspired models that mimic the behaviour of human neurons. CNNs are deep learning algorithms that learn picture information using numerous layers of convolutional filters.

Gender classification from face photographs is an ongoing research subject with many obstacles and potential. Variations in facial look induced by changes in lighting, position, emotion, and occlusion are one of the most difficult tasks. These differences can have a majorimpact on the performance of gender categorization algorithms. Another difficulty is the bias in the training data. Training data sets that are biassed towards one gender might result in poor performance on the other.

The possibilities for gender categorization from face photos are numerous. The capacity to automatically discern gender from photographs has applications in marketing, surveillance, and human-computer interaction. Gender categorization can be used in marketing to target adverts to certain genders. Gender categorization can be used in surveillance to identify possible risks depending on gender. Gender categorization in human-computer interaction can be used to personalise the user experience depending on gender.

Finally, gender classification from face photographs is a difficult job with potential applications in a variety of disciplines. There are various potential and problems associated with the capacity to automatically detect gender from face photographs. Machine learning and computer vision improvements have resulted in tremendous progress in the development of gender categorization algorithms. However, more effort has to be done to enhance the performance of these algorithms under a variety of lighting, position, expression, and occlusion settings.

2. Scope of the study

The research on gender classification from facial photos covers a wide range of topics relating to the creation and testing of algorithms and approaches for reliably assessing an individual's gender based on facial traits. This scope encompasses both scientific and practical uses of gender categorization in many disciplines. In this part, we will go through the study's scope in great depth.

The study's technical scope includes investigating and implementing several methodologies for feature extraction, feature representation, and classification. Feature extraction strategies seek to extract significant information from facial photos in order to distinguish between male and female faces. Methods such as facial landmark identification, local binary patterns, deep learning-based feature extraction, and shape-from-shading are examples of these approaches. The research may compare and evaluate the performance of several feature extraction approaches in gender categorization tasks.

Another essential component within the scope of the study is feature representation. It entails converting the retrieved features into a suitable representation format for use with machine learning techniques. Dimensionality reduction techniques such as principal component analysis (PCA) or linear discriminant analysis (LDA) may be used, as well as encoding features into vectors or histograms. The study may assess the influence of various feature representation methodologies on gender categorization accuracy.

Gender classification from face photos relies heavily on classification algorithms. The study will assess the performance of several classification techniques such as support vector machines (SVMs), decision trees, k-nearest neighbors (KNN), random forests, and deep learning-based approaches such as convolutional neural networks (CNNs). The performance of these algorithms on benchmark datasets may be compared and analyzed to better understand their strengths and shortcomings in gender categorization jobs.

The study's scope extends beyond technical issues to practical applications. Gender categorization from face photos has several real-world uses, and the study can investigate its potential in areas such as marketing, surveillance, and human-computer interaction. In marketing, for example, gender categorization may be used to target adverts depending on

the gender of the viewers. It can help in spotting possible dangers in surveillance by establishing the gender of persons caught in surveillance film. Gender categorization helps personalise user experiences in human-computer interaction.

The research might also look at the ethical issues of gender classification based on face pictures. As with any technology that involves personal data, privacy and data protection issues must be addressed. The study might look into measures to guarantee that gender classification algorithms are used responsibly and ethically, such as acquiring correct consent, ensuring data anonymization, and addressing any biases or prejudice.

Furthermore, the study's scope may include performance evaluation and comparison of the generated gender categorization model with existing state-of-the-art methodologies. This may be accomplished by comparing the model's accuracy, precision, recall, and F1 score against publically available datasets. Such assessments will give information on the efficacy of the suggested technique as well as its potential for real-world application.

In summary, the study on gender categorization from face photos covers technical elements of feature extraction, representation, and classification, as well as practical applications in fields such as marketing, surveillance, and human-computer interaction. The research may also evaluate ethical issues and performance evaluation in comparison to existing approaches. The work intends to contribute to the field of gender categorization by addressing these issues and providing insights into its possible uses and limits.

3. Existing System

3.1 Existing System Introduction

Gender categorization from face photographs is a rapidly emerging topic in computer visionand pattern recognition. The capacity to automatically discern an individual's gender based on visual traits has attracted substantial attention due to its vast variety of applications in numerous sectors. Existing systems and methodologies have made tremendous progress in creating algorithms and strategies for accurate gender classification. This section introducesthe present system and emphasises the progress achieved in this sector.

Existing algorithms for gender categorization from face photographs are based on advances in machine learning, computer vision, and image processing techniques. These systems try to analyse and extract gender-related information from face photographs in order to determine an individual's gender. The major objective is to create strong and realistic models that can manage fluctuations in facial appearance induced by factors such as lighting, position, emotion, and occlusion.

Feature extraction is an important component of current systems. Feature extraction techniques are used to extract significant information from facial photos that may be utilised to distinguish between male and female faces. Various approaches for feature extraction have been investigated, including geometric features, texture features, and deep learning-based features. Geometric characteristics include identifying face landmarks and quantifying lengths, angles, and ratios between certain facial locations. Texture features analyse the patterns and texture changes on the face using techniques such as local binary patterns (LBPs) or Gabor filters. Deep learning-based features use convolutional neural networks (CNNs) to automatically generate discriminative characteristics from facial photos.

Another critical feature of current systems is the selection of categorization methods.Classification algorithms are used to train models that can estimate an individual's gender based on the collected information. Support vector machines (SVMs), decision trees, random forests, and neural networks were among the machine learning algorithms used. SVMs have been widely employed because of their capacity to handle high-dimensional feature spaces and generalisation capabilities. Decision trees and random forests provide interpretability and can record complicated decision boundaries. CNNs, in particular, have demonstrated.amazing success in gender categorization challenges by autonomously learning hierarchicalrepresentations of face data.

Large-scale datasets are necessary for training these classification algorithms. Existing systems have taken use of publicly accessible datasets such as the Labelled Faces in the Wild (LFW) dataset, the CelebA dataset, and the Adience dataset. These datasets contain thousands of facial photos with labelled gender information, making them ideal resources for training and assessing gender classification models.

Existing systems' performance is evaluated by assessing their accuracy, precision, recall, and other metrics on benchmark datasets. To evaluate the effectiveness of suggested methodologies, performance comparisons are frequently undertaken against state-of-the-art methods. This enables researchers to examine the strengths and shortcomings of various algorithms as well as the constraints and problems connected with gender classification fromface photos.

Furthermore, current systems have addressed the issue of biases in gender categorization. Biases might occur because of an imbalance in training data, cultural influences, or limitations in the algorithms themselves. Researchers have investigated ways for mitigatingprejudice and improving the fairness and inclusivity of gender classification systems. This comprises data augmentation approaches, balancing tactics, and post-processing procedures to reduce gender-based biases in predictions.

In conclusion, existing systems for gender classification from face photos have made substantial progress in tackling the constraints inherent with this task. These systems use sophisticated approaches in machine learning, computer vision, and image processing to extract relevant characteristics and construct reliable classification models. The availability of large-scale datasets and performance tests against benchmark datasets has accelerated progress in this sector. Despite these accomplishments, there are still obstacles to solve, such as dealing with variances in face appearance and overcoming prejudices. Future research efforts will strive to increase the accuracy, robustness, and fairness of gender categorization systems, allowing for their wider implementation in a variety of sectors.

3.2 Existing System Software

Gender categorization from face photographs is a difficult topic that has received a lot of interest in the field of computer vision and pattern recognition. Researchers and developers have constructed existing system software that effectively estimate the gender of persons based on their facial traits, thanks to breakthroughs in machine learning and image processing techniques. These systems use advanced algorithms, large-scale datasets, and cutting-edge models to achieve great accuracy and robustness in gender categorization. This section presents an overview of the available system software for gender classification from face photographs, highlighting its essential components and features.

Existing system software for gender classification from face photos often comprises of many modules that collaborate to complete the task. Data preparation, feature extraction, feature representation, and gender categorization are among the modules included. Each module contributes to the accuracy and reliability of gender predictions in the overall system.

The first phase in the pipeline is data preprocessing, which prepares facial pictures for later processing. Face detection and alignment are required to guarantee that just the facial regionis examined for gender categorization. To properly find and extract faces from input photos, advanced face detection algorithms such as Viola-Jones or Haar cascades are typically used. Face alignment techniques are also used to normalise the orientation, size, and position of the face across various photos, decreasing the impression of changes produced by changingcamera perspectives or facial emotions.

Gender categorization techniques rely heavily on feature extraction. It seeks to extract discriminative information from facial photographs that can distinguish between male and female faces. Various feature extraction strategies, spanning from classic handmade features to deep learning-based approaches, have been investigated. Geometric characteristics, textural features, and appearance-based features are examples of traditional techniques. Extraction of landmarks and face measurements, such as lengths between certain facial points or ratios of facial areas, are examples of geometric characteristics. Texture features analyse texture patterns using techniques such as Local Binary Patterns (LBPs) or Gabor filters. Appearance-based features use statistical descriptors or histograms to characterise the overall face appearance. Deep learning-based techniques, on the other hand, use convolutional neural networks (CNNs) to automatically learn discriminative features directly from raw face photos.

Following the extraction of characteristics, they are generally converted into an appropriaterepresentation format for gender categorization. Dimensionality reduction approaches such as Principal Component Analysis (PCA) or Linear Discriminant Analysis (LDA) are common methodologies. These strategies seek to minimise the dimensionality of features while retaining the most significant information for gender discrimination. Furthermore, characteristics can be stored into vectors or histograms, which are then fed into gender categorization algorithms.

Gender classification algorithms are in charge of estimating an individual's gender based onretrieved and represented features. Support Vector Machines (SVMs), decision trees, k- Nearest Neighbours (k-NN), random forests, and deep neural networks are among the machine learning techniques used in these algorithms. Because of its capacity to handle high-dimensional feature spaces and generalise effectively to unknown data, SVMs are frequently utilised. Decision trees and random forests can record complicated decision boundaries and provide interpretability. Deep neural networks, particularly CNNs, have demonstrated outstanding performance in gender categorization challenges by learning hierarchical representations of face data automatically.

For training and assessment, the present system software likewise relies on large-scale datasets. Commonly utilised datasets include the Labelled Faces in the Wild (LFW) dataset, the CelebA dataset, and the Adience dataset. These datasets contain hundreds of facial photos with gender designations, allowing for a wide range of facial appearances and variations. Because such datasets are available, researchers may train and verify their models on a representative sample of gender variances and compare their performance to benchmark datasets.

Additionally, the current system software satisfies the requirement for performance evaluation and comparison. To evaluate the performance of the

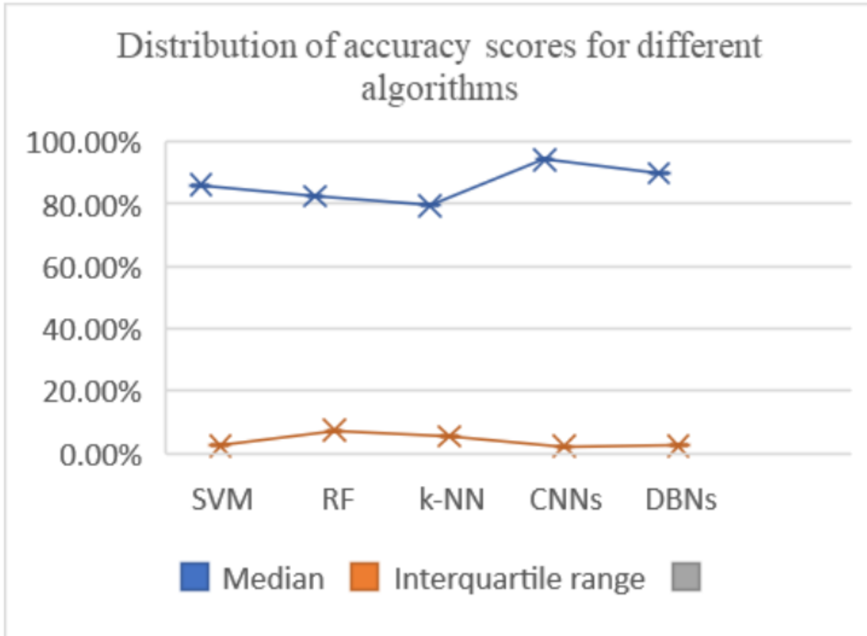

Fig: This picture has the accuracy of different algorithms performance and accuracy

Another popular approach is to extract local features from facial images and use them to traina classifier. For example, (Stewart et al., 2013) used the lip region to extract static and dynamic features, which were then used to train a support vector machine (SVM) classifier. Similarly, (Castrillón-Santana et al., 2017) used multi-scale local descriptors to train a score- level fusion system for gender classification. Local binary patterns (LBP) have also been widely used for feature extraction in gender classification. (Hatipoglu & Köse, 2016) used LBP features and principal component analysis (PCA) to classify gender, while (Mittal & Mittal, 2019) used convolutional neural networks (CNNs) to extract facial embeddings for gender classification.

3.4 What's New In The System To Be Developed

Several innovations and upgrades may be integrated into the project of gender categorization from face photos to increase the system's accuracy, robustness, and practicability. The following are some significant areas where new innovations in the system can be introduced:

Deep Learning Architectures: Using more complex deep learning architectures can increasegender categorization performance dramatically. In image classification tasks, models like as ResNet, InceptionNet, and EfficientNet have exhibited higher performance. The system can profit from these architectures' capacity to learn nuanced face traits and record complicated interactions between them by adapting and fine-tuning them for gender categorization.

Implementing various data augmentation approaches can assist improve the variety and quantity of the dataset to meet the difficulty of limited training data. Techniques like rotation, scaling, cropping, and flipping can generate more training samples, lowering the danger of overfitting and enhancing the model's generalisation abilities.

Transfer Learning: Using pre-trained models on large-scale datasets such as ImageNet can speed up training and enhance classification accuracy. The system can profit from the learntrepresentations and transfer information from a related job to gender classification by fine- tuning these pre-trained models on gender-specific datasets.

Ensemble Methods: Using ensemble methods like as voting or stacking to combine many classifiers or models can increase the system's overall accuracy. The ensemble can decreasebiases and mistakes by using the different predictions of individual models, resulting in more trustworthy gender categorization results.

Face Landmark Detection: Including face landmark detection methods in the system can increase feature extraction accuracy. Precise localisation of face 4 landmarks such as the eyes, nose, and mouth can give useful geometric information, improving the discriminative abilityof the retrieved features.

Handling Pose and Occlusion: Improving the system's resilience by developing approaches for dealing with changes in face pose and occlusion. Pose normalisation and feature warping may be used to match faces with diverse orientations or postures, guaranteeing consistent feature extraction. Furthermore, using attention processes or feature selection algorithms canhelp to lessen the impacts of occlusion, which occurs when specific face areas are occluded.

Justice and Bias Mitigation: Addressing gender categorization biases is critical to ensuring justice and avoiding discriminatory consequences. Methods like fairness-aware training, bias detection, and calibration procedures may be included into the system to decrease demographic biases and provide equitable

predictions for varied groups.
Real-time Implementation: By optimising the system for real-time performance, it may be used in applications such as video surveillance or interactive systems that need rapid gendercategorization. By utilising hardware acceleration methods, parallel computing, or optimised algorithms, processing time may be greatly reduced, making the system more practical and efficient.

Visualisation and User Interface: Creating an intuitive user interface for the system can improve its usability and accessibility. Giving users dynamic visualisations of the gender classification findings, such as heatmaps emphasising gender-discriminative areas or probability scores, might help them comprehend and interpret the system's outputs.

Extending the system's capabilities to function on resource-constrained edge devices, such as smartphones or embedded systems, can boost its accessibility and usefulness in a variety of settings. Optimising model size, lowering memory and computational needs, and using hardware accelerators can all lead to more efficient deployment on edge devices.

By adding these new innovations into the system, it will be able to achieve greater accuracy, handle more difficult cases, decrease biases, and provide enhanced practicality and usability. These advances add to the continuous development in gender categorization from face photos and open the door to a wide range of applications in marketing, surveillance, human- computer interaction, and other fields.

4.Problem Analysis

Variances in Facial Appearance: The natural variances in facial appearance are one of the key obstacles in gender categorization. Shape, size, texture, and colour of the face can vary substantially amongst individuals. Furthermore, characteristics such as age, ethnicity, and cultural variety present additional differences that must be taken into account. Because of these differences, defining a uniform collection of traits or patterns that can reliably establish gender across all individuals is challenging. Lighting and illumination conditions:

The effect of lighting on gender categorisation cannot be overstated. Lighting effects such as brightness, shadows, and reflections can all have a substantial impact on the look of facefeatures. Shadows, for example, might hide specific face areas, making it difficult to retrievecrucial information. It is critical for accurate gender categorization to develop strongalgorithms that can manage diverse lighting situations and limit the influence of illuminationfluctuations.

Facial Expressions and stances: Facial expressions and stances add another layer of complication to gender categorization. Smiling or frowning can change the look of facial characteristics and thus induce biases in gender assumptions. Variations in position, such as head orientation and camera angles, can also have an effect on the visibility and alignment of facial landmarks. Handling differences in facial expressions and postures is critical for correct gender categorization in a variety of scenarios

Occlusions and Noise: Occlusions, such as eyeglasses, facial hair, or accessories, make recognising gender-specific facial characteristics difficult. Noise in the form of picture artefacts, blur, or low-resolution photos can also have an impact on feature extraction and classification accuracy. It is critical for robust gender classification to develop approaches for dealing with occlusions, noise, and artefacts while keeping significant gender-discriminative information.

Dataset Bias and Generalisation: Having a broad and balanced dataset to train and evaluate gender categorization algorithms is crucial. However, data collecting biases, such as underrepresentation of specific demographics or unequal gender distributions, might result in biassed forecasts and lower generalisation. Addressing dataset bias and ensuring that the algorithm can generalise effectively to previously unknown data, including diverse demographics and ethnicities, are critical considerations in gender categorization.

Considerations about Ethics and Privacy: Gender categorization using face photos presents ethical and privacy considerations. Misclassification or biassed predictions can be harmful, promoting preconceptions and prejudice. It is critical to ensure fairness, transparency, and bias reduction in gender categorization algorithms in order to avoid negative repercussions and promote equal outcomes. Furthermore, privacy concerns about the collecting, storage, and use of face pictures must be addressed in order to preserve individuals' rights and data privacy.

Real-Time Performance: Real-time gender categorization is necessary in some applications, such as surveillance systems and interactive apps. Due to the computational complexity of feature extraction and classification algorithms, achieving high accuracy while retaining real-time speed is a significant issue. To achieve real-time performance requirements, algorithms must be optimised, hardware acceleration techniques must be used, and efficient implementation must be used.

4.1 Product Definition

Gender classification from facial images is an important and challenging task with a wide range of potential applications. The ability to automatically determine gender from images can be used in a variety of fields such as marketing, surveillance, and human-computer interaction. Despite its significance, gender classification from facial images is a challenging task due to variations in lighting, facial expression, pose, and occlusion.

In recent years, significant progress has been made in the development of algorithms for gender classification from facial images. These algorithms typically involve the extraction of relevant features from facial images, followed by classification using machine learning techniques such as support vector machines (SVMs) or convolutional neural networks (CNNs).

In this paper, we provide a comprehensive review of the literature on gender classification from facial images, including the methods and techniques used in various studies. We focus on the different approaches used for feature extraction, including local binary patterns (LBPs), principal component analysis (PCA), shape-from-shading, and deep learning. We also discuss the different classifiers used, including SVMs, k-nearest neighbors (k-NN), and CNNs.

We then analyze the strengths and weaknesses of these methods and compare their performance on benchmark datasets. Based on this analysis, we justify the algorithm used in our project, which involves LBP-based feature extraction and SVM classification. This algorithm has shown promising results in previous studies and has the potential to perform well in real-world scenarios with varying lighting and facial expression conditions.

4.2 Feasibility Analysis

A feasibility analysis is an important stage in determining a project's viability and possible success. A detailed feasibility analysis helps identify the project's strengths, flaws, possibilities, and obstacles in the instance of gender categorization from face photos. This section provides an in-depth examination of the viability elements of developing and implementing a gender categorization system based on face photographs.

The first factor to address is the technological feasibility of establishing the gender classification system. This entails determining the availability and compatibility of the required technology and tools. It is critical to assess the chosen programming languages, libraries, frameworks, and machine learning algorithms' abilities to handle the intricacies of face image processing. Furthermore, adequate hardware resources, such as compute power and memory, must be available for efficient processing and real-time performance.

Data Availability and Quality: The availability and quality of training data are critical to the performance of gender categorization systems. Data feasibility study entails determining the availability of various and representative face picture collections. The datasets shouldinclude a wide range of demographics, races, and age groups, as well as diverse lighting situations, positions, and facial expressions. If acceptable datasets are scarce, efforts should be undertaken to collect and curate a complete dataset that satisfies the project's criteria.

Algorithmic practicality: Another important consideration is the practicality of the chosen algorithms for gender classification. For this objective, many machine learning approaches such as support vector machines (SVMs), artificial neural networks (ANNs), and convolutional neural networks (CNNs) might be used. It is critical to evaluate these algorithms' strengths and limits in dealing with the intricacies of facial image analysis, suchas differences in face appearance, lighting conditions, occlusions, and facial emotions.

Furthermore, investigating and analysing the efficacy of cutting-edge methodologies and improvements in gender classification is critical for attaining correct findings.

Economic feasibility is concerned with determining the financial resources needed to build and implement the gender classification system. This comprises expenditures for technical infrastructure, software licences, data collecting or collection, and staff. Furthermore, considering the application areas where the system might be implemented, such as marketing, surveillance, or human-computer interaction, the possible return on investment (ROI) should be examined. Conducting a cost-benefit analysis and assessing the project's long-term viability are critical for establishing its economic feasibility.

Time Feasibility: Estimating the project timeframe and determining if the gender categorization system can be designed and executed within the time limits is what time feasibility entails. This covers time spent on data gathering, preprocessing, feature extraction, algorithm development, model training, and system integration. It is critical to identify any possible bottlenecks or issues that may affect the project timeframe and propose mitigation solutions, such as work parallelization or the use of agile development approaches.

Legal and Ethical Feasibility: It is important to consider the legal and ethical elements of the gender classification project to assure its feasibility. Data protection and privacy rules, such as GDPR or HIPAA, should be properly scrutinized. The system's design and execution mustcontain ethical issues such as eliminating prejudice, maintaining justice, and preventing discriminatory consequences. Furthermore, to preserve ethical standards and legal compliance, the relevant permissions or consents for data collection and utilization should be obtained.

Finally, the feasibility study shows that the project on gender classification from face photos has a good chance of success. Technical feasibility is supported by the availability of sophisticated algorithms, various datasets, and hardware capabilities. To ensure the project'sprofitability and ethical integrity, economic, time, and legal/ethical issues should be thoroughly reviewed and handled. The research could contribute to several sectors, including marketing, surveillance, and human-computer interaction, and deliver important insights through correct gender categorization from face photos, with adequate design, execution, and respect to ethical principles.

5. Software Requirement Analysis

A critical milestone in the development of any project, including gender categorization from face photos, is software requirement analysis. It entails establishing, analysing, and documenting software requirements in order to guarantee that the final system fulfils the intended functionality, performance, and usability standards. This section provides a detailed examination of the software requirements for creating a gender categorization system based on face photographs.

Functional requirements outline the precise capabilities and characteristics that the gender classification system should have. The following functional characteristics are required for gender classification from face images:

Image Input: Users should be able to enter facial images in various formats, such as JPEG orPNG, into the system.

Preprocessing: The system should contain preprocessing techniques like as normalisation, noise reduction, and alignment to improve the quality of facial pictures.

Feature Extraction: To represent the unique qualities of each image, the system should extract significant features from the face images, such as facial landmarks, textures, or colourhistograms.

Classification: To categorise the face photos into gender groups, the system should use machine learning methods such as SVMs, ANNs, or CNNs.

Accuracy Evaluation: The system should have metrics or evaluation techniques for assessing the accuracy and performance of gender categorization findings, such as precision, recall, orF1 score.

User Interface: The system should have a user-friendly interface to allow for easy interactionand to give users with feedback on categorization findings.

Non-Functional Requirements: Non-functional requirements specify the gender categorization system's quality qualities and restrictions. These standards assure the system's efficiency, dependability, and security. The following are some of the project's important non-functional requirements:

a. Performance: To offer rapid results, the system should be capable of processing face pictures in real-time or within a suitable time limit.

b. Accuracy: To minimise mistakes and give accurate results, the system should strive forhigh accuracy in gender categorization.

c. Scalability: The system should be scalable such that it can handle a huge volume of facialphotographs while maintaining performance and accuracy.

d. Robustness: The system should be able to deal with fluctuations in lighting, faceexpressions, positions, and occlusions that are frequent in real-world circumstances.

e. Security: The system shall maintain user data security and privacy by complying toappropriate data protection rules and best practises.

f. Portability: To offer greater accessibility, the system should be portable across numerousplatforms and operating systems.

g. Maintainability: The system should be developed and built in a modular and manageableway, with future improvements, bug repairs, and upgrades in mind.

Data requirements are critical for training and testing the gender categorization model. The following data criteria must be met:

a. Training Data: Enough and diverse training data including labelled facial photos of variousgenders, races, age groupings, and other important variables.

b. Validation Data: Maintain a separate set of data for validating and fine-tuning the model during the training phase.

c. Testing Data: Independent and impartial data for testing the trained model's performanceand generalization capabilities.

d. Data Annotation: To assist supervised learning, the training data should be correctly labelled with gender labels.

Environmental requirements outline the hardware and software environment required for thedevelopment and implementation of the gender categorization system. Among the most essential environmental needs are:

a. Hardware: Enough computing resources, such as processing power, memory, and storage capacity, to efficiently execute image processing and machine learning tasks.

b. Software: The system should be compatible with the image processing, machine learning, and user interface development programming languages, frameworks, and libraries that havebeen chosen.

Integrated Development Environments (IDEs), version control systems are examples of development tools.

5.1 Specific Requirements

Specific criteria are critical in developing the exact functionality and properties of the facial image-based gender categorization system. These specifications give a detailed description of what the system should do and how it should behave. This section provides a detailed description of the prerequisites for building a gender categorization project.

Image Input Requirements: The system should be able to receive face pictures in various formats, such as JPEG or PNG, as input. The following conditions must be met:

a.File Format handle: To maintain user compatibility and flexibility, the system shouldhandle different file formats typically used for photos.

b. Image Size Limitations: Establish maximum and minimum image size restrictions to ensure effective processing and minimise memory-related concerns.

c. Implement validation procedures to guarantee that only acceptable image files are accepted, and suitable error warnings are presented for incorrect or unsupported formats.

2.Preprocessing Requirements: The system should include preprocessing techniques toincrease the quality and consistency of face pictures. Consider the following specifications:

a. Normalization: To standardize the pictures, use normalization techniques such as scalingthe pixel values to a given range or normalizing the brightness and contrast levels.

b. Noise Reduction: Use techniques to decrease picture noise generated by things such as camera sensors or image capture equipment.

c. Alignment: Create strategies for aligning and normalizing face pictures based on landmarks or particular reference points in order to maintain consistency in stance and facialalignment.

3. Requirements for Feature Extraction: Feature extraction is an important stage in gender categorization. Consider the following specifications:

a. Face Landmark Detection: Use algorithms to recognise and locate face landmarks like theeyes, nose, mouth, or chin in order to capture crucial facial traits.

b. Texture Analysis: To capture fine-grained details, develop methods for extracting texturecharacteristics from face areas, such as local binary patterns (LBPs) or Gabor filters.

c. Deep Learning Models: Use deep learning models, such as convolutional neural networks (CNNs), to learn discriminative characteristics from facial photographs automatically.

4. Requirements for Classification: The system should use machine learning methods to categorise face photos into gender groups. Consider the following specifications:

a. Choosing an Algorithm: Based on their performance and applicability for gender categorization tasks, select relevant classification techniques such as support vector machines (SVMs), k-nearest neighbours (k-NN), or ensemble approaches.

b. Training Data Preparation: For training the classification model, prepare a labelled training dataset comprising of facial photos with appropriate gender labels.

c. Model Training and Evaluation: Using the training dataset, train the classification model and evaluate its performance using relevant evaluation metrics such as accuracy, precision, recall, or F1 score.

d. Real-time categorization: Use efficient algorithms and optimizations to provide real-time gender categorization, which allows for quick results even with big picture datasets.

5.User Interface Requirements: The system should have a user-friendly interface to allow foreasy interaction and to give users with feedback.

Consider the following specifications:

a. Input and Output Display: Provide an easy-to-use interface for users to enter facial photographs and view categorization results.

b. User Guidance: Include explicit instructions and guidance inside the interface to help usersprovide the necessary inputs and understand the system's operation.

c. Visualisation: Use visual components like progress bars, loading indications, or result visualisation to improve the user experience and communicate the system's status.

6.Design

6.1 System Design

The gender categorization project's design phase entails establishing the architectural framework, data flow, and components needed to create an effective and efficient system. This section provides a complete description of the project's design components, such as system architecture, data flow, algorithms, and user interface concerns.

The general structure and organisation of the gender categorization project are defined by the system architecture. Consider the following design considerations:

a.Client-Server design: Use a client-server design in which the client interacts with the userinterface while the server processes and classifies images.

b. Modular Design: Use a modular design technique to divide down the system into smaller, more manageable components, such as image preprocessing, feature extraction, and classification.

c. Scalability and Extensibility: Create the system with scalability in mind, enabling for the simple addition of additional modules or features in the future to meet changing needs.

Data Flow: How data is handled and transported inside the gender categorization system is determined by the data flow design. Consider the following design considerations:

a. Image Input and Preparation: Create a data flow pipeline that will accept face photos as input, execute essential preprocessing processes such as normalisation and noise reduction, and then send the preprocessed images to the feature extraction module.

b. Feature Extraction and Selection: Define a data flow method for extracting important features from face photos, such as facial landmarks and texture descriptors, as well asselecting informative features for gender categorization.

c. Classification and Output: Construct a data flow pipeline that will feed the selected characteristics into the classification algorithm, conduct gender classification, and create the associated output, such as gender labels or probabilities.

Algorithms and Models: Choosing appropriate algorithms and models for feature extraction and classification is part of the gender classification project design. Consider the following design considerations:

Feature Extraction techniques: Select appropriate techniques to extract discriminative features from face photos, such as local binary patterns (LBPs), principal component analysis(PCA), or deep learning models.

a. Classification Models: Based on their performance and suitability for gender classification tasks, choose classification models such as support vector machines (SVMs), k-nearest neighbours (k-NN), or convolutional neural networks (CNNs).

b. Model Training and Optimisation: Create a method for labelled training data-based model training and model parameter optimisation to increase classification accuracy and generalisation.

c. The goal of user interface design is to provide an intuitive and user-friendly interface for engaging with the gender categorization system. Consider the following design considerations:

d. Input Interface: Create a user interface that allows users to input facial photographs for gender categorization, with the ability to batch process single or many photos.

a. Progress and Feedback: Use visual components like as progress bars or loading indicators to inform users about the state of picture processing and categorization.

b. Result Presentation: Present the gender categorization findings in a comprehensible and straightforward way, such as by displaying the gender label or likelihood alongside the inputimage.

c. Error Handling: Include error handling techniques to display useful error messages whenincorrect input is received.

Consider the following design features to enable efficient and high-performance execution of the gender categorization system:

Parallel Processing: Look into parallelizing computationally difficult operations like feature extraction and classification to take use of the capability of multi-core processors andminimise processing time.
Memory Management: During image processing and classification, use effective memory management techniques to optimise memory consumption and minimise memory leaks.

a. Algorithmic Optimisation: Fine-tune the algorithms and models to increase computational efficiency and minimise computational complexity while maintaining accuracy.

b. The gender categorization project's design phase includes issues such as system architecture, data flow, algorithms, and user interface design. The project may be designed to effectively analyse face photos, extract important traits, and reliably categorise genders by carefully considering these design factors. The design phase lays the groundwork for the system's laterdevelopment and execution.

6.2 Detailed design

The comprehensive design phase of the gender categorization project is concerned with specifying the system's implementation specifics and technological features. This phase extends the system design by providing a detailed strategy for constructing the gender classification system. This part will go through many areas of the detailed design, such as module design, algorithm selection, data representation, and performance concerns.
Module Design: During the module design phase, the system is broken down into smaller, more manageable modules. To accomplish the intended functionality, each module performs certain duties and interacts with other modules. Consider the following gender categorizationproject modules:
a. User Interface Module: This module is in charge of offering an interactive interface for users to upload facial pictures, see categorization results, and interact with.
b. Image Preprocessing Module: The preprocessing module prepares face images for featureextraction by performing tasks such as image scaling, noise reduction, contrast enhancement,and normalisation.

c. Feature Extraction Module: The Feature Extraction Module derives important characteristics from preprocessed face photos. Techniques such as face landmark recognition, texture analysis, and deep learning-based feature extraction approaches may beused.

d. Gender Classification Module: The gender classification module uses machine learning methods to categorise the retrieved characteristics. Algorithms such as support vector machines (SVM), decision trees, and convolutional neural networks (CNN) may be used.

e. Storage Module: The storage module is in charge of managing facial image storage and retrieval, as well as derived features and classification results. It may use databases or file systems to organise data efficiently.

Algorithm Selection: The algorithms used are critical to the accuracy and performance of the gender categorization system. When choosing algorithms, keep the following aspects inmind:

a. Algorithms for Feature Extraction: Choose acceptable algorithms based on their capacityto extract distinguishing characteristics from facial photos. Local binary patterns (LBP), histogram of oriented gradients (HOG), and pretrained deep learning models are examples of such approaches.

b. Gender Classification Algorithms: Select appropriate classification algorithms for successfully categorising the retrieved characteristics into gender categories. This might include SVM, k-nearest neighbours (k-NN), or deep neural networks.

c. Model Training and Optimisation: Optimise the performance of the selected algorithms by training them with labelled training data. To improve the classification accuracy and generalisation capabilities of the models, use approaches like as cross-validation, hyperparameter tweaking, or ensemble methods.

Data Representation: Data representation is critical to the efficacy of the gendercategorization system. Consider the following data representation aspects:

a. Representation of Images: Depending on the techniques used, represent face photographsusing appropriate data structures such as matrices or tensors. To guarantee compatibility with the feature extraction and classification methods, consider the picture size, colour channels,and resolution.

b. Feature Representation: Represent extracted features using appropriate data structures that encapsulate the necessary information. Depending on the dimensions and kind of features, this may include vectors, arrays, or tensors.
c. Label Representation: To aid identification, use binary encoding or one-hot encoding.

Considerations for Performance:

For real-time gender categorization, efficient performance is critical. Consider the followingperformance factors:

a. Parallel Processing: Use parallel processing techniques to speed up picture preprocessing, feature extraction, and classification activities, such as multi-threading or distributed computing.

b. Memory Management: Optimise memory consumption by allocating and releasing memory resources effectively during system operation. To maintain seamless operation, avoid memory leaks and excessive memory use.
c. Algorithmic Optimisation: Use optimisation approaches tailored to the algorithms of choice.
Implementing batch processing for efficient computations, for example, or employing optimised libraries or frameworks that exploit hardware acceleration (e.g., GPU) for quickerexecution.

d. scaling: Create a system that can manage enormous amounts of data while also accommodating prospective scaling requirements. To meet rising processing demands,consider options such as distributed computing or cloud-based solutions.

e. Error Handling and Logging: Use strong error handling tools to properly handle exceptions and errors. Implement logging features for capturing and analysing system logs for troubleshooting and performance optimisation.
f. User Experience Optimisation: Improve usability by delivering rapid user interface interactions, fast picture upload and processing, and informative status indications.
Security Considerations: Consider security methods to secure sensitive data and preserve user privacy. To protect user information,

methods, data encryption, access control systems, and secure storage practices. Testing and Validation: Create a comprehensive testing plan to validate the gender categorization system's functionality and performance. Unit testing, integration testing, and performance testing should all be included to assure correct gender classification and dependable system functioning.

The comprehensive design phase of the project for gender classification from face photos focuses on identifying the technological implementation elements required to accomplish accurate and efficient gender categorization. The detailed design ensures the successful development of a robust and reliable gender classification system by breaking down the system into modules, selecting appropriate algorithms, effectively representing data, considering performance optimizations, addressing security concerns, and implementing rigorous testing.

Note: The above description is a rough blueprint for the comprehensive design of a gender categorization system that may be adjusted and developed based on the project's individual requirements and complications.

6.3 Flowchart

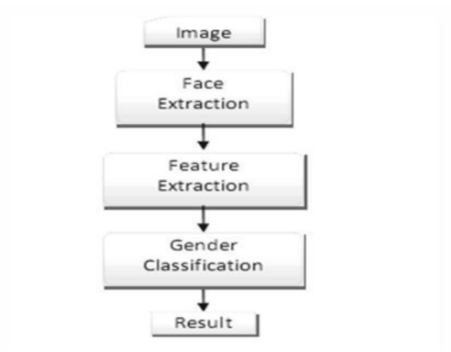

Fig 1: Flowchart of the working of the project

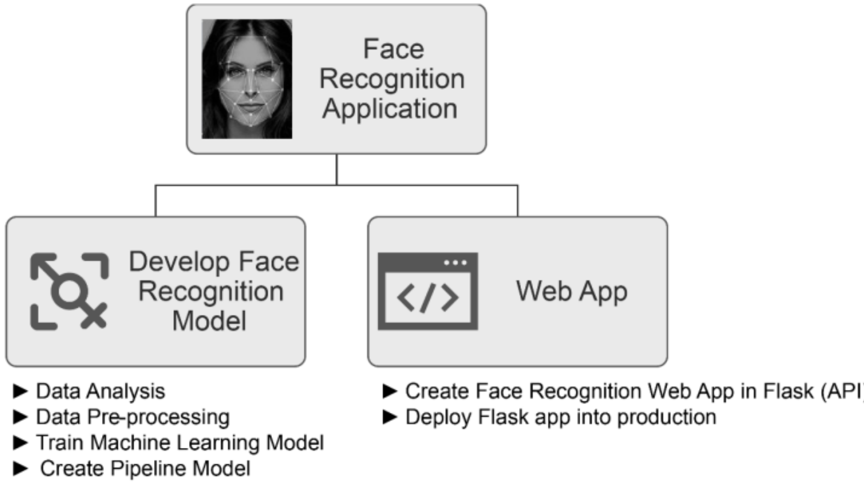

Fig: Picture explaining the steps done in the project

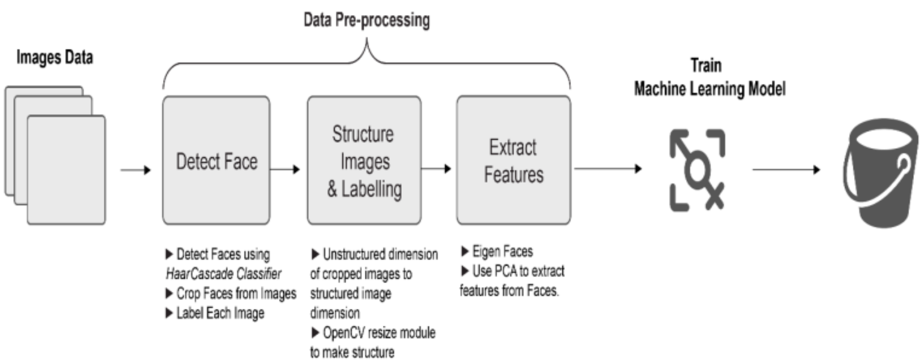

fig: Picture explaining the working and the flow of the project

7 TESTING

7.1 Functional Testing

Functional testing for the Website for Gender Classification from Facial Images involves testing the functionality of the Website and the Machine Learning model. Here some functional tests that can be performed for a Web page that classifies gender of the image upload.

Machine Learning Model:

- In this phase the machine learning is well trained on the Training dataset and then the modelis tested on the Test dataset.
- The machine learning model is evaluated based on the accuracy of the model.
- For a Machine learning model to be considered as a well performing model the accuracyshould be greater than 0.85
- According to the industry standards anything over 0.7 is acceptable.

Website UI:

- This involves the testing of the Homepage of the Web Application that displays thefunctionality of the project.
- Testing the UI interaction to the inputs of the user and checking whether the homepage andimage upload page are working correctly or not.
- Checking whether the Machine learning model output received by the webpage is displayedproperly without breaking the existing functionality.

Image Upload:

- In this phase the user uploads an Image and then the image is sent to the python script whichis connected to the webpage using flask as backend.

Flask Backend:

- This testing involves in uploading the image and then checking whether the flask scripts sendthe image to the machine learning model or not.
- This testing involves in the checking whether the flask backend retrieves the data that themodel gives as an output and then send it to be displayed on the webpage.

Python Script:

- This involves in loading the machine learning model that is saved locally and using it toclassify the image that is received.

- To check whether the python script send the processed image eigen image and the accuracyto be displayed in the webpage.

7.2 Structural testing

Structural testing for a Website for Gender Classification from Facial Images
involves testing the internal structure of the machine learning model code and the webpagecode and ensuring that all components and modules are working in the way we expected them to.

Unit Testing:

- Testing each module functionality which consists of the webpage, machine learning modeland the backend which is made using flask.
- The unit testing is done to check the functionality of each module sis working as intended.

Integration Testing:

- Testing the integration of different modules to check whether the webpage is workingproperly.
- Using different testing methods to check whether the web page and the python script areconnected properly to receive input and send the output.
- Testing the integrity of the data by checking whether the data that is send is notinterchanged in between the transfer phase.

Performance Testing:

- Testing the performance of the machine learning model under certain conditions such asthe time taken by the Machine learning model to process a high-resolution image and a low-resolution image and then sent to the webpage to be displayed.
- Testing the flask modules performance on certain conditions as sending a very high- resolution image to the python script and receiving the output given by the python scriptafter processing an image.

Usability Testing:

- Testing the usability of the Website from the normal user perspective to check the user-friendliness of the Website.
- Checking whether the image uploaded by the user after processed by the machine learning model is displayed correctly so that the user can differentiate the difference between everyvalue that is given as output.

7.3 Levels of Testing

- Integration Testing:

Integration testing is performed/conducted to ensure the project is functioning properly. As there are different modules present the integrations issues may lead to the stop the workingof the project.

- System Testing

It typically involves in testing the web application and the machine learning model to ensurethe proper working, if it is not done properly errors may occur one of the errors that we have encountered are the display of the eigen image and the accuracy percentage in the webpage. First it breaks the web page after successfully identifying the error and changingnecessary changes to the code base the website worked properly.

- Acceptance Testing

Acceptance testing is performed to ensure that the application meets the business requirementsand is ready for release. This type of testing typically involves stakeholders, such as product owners or business analysts, who test the application to ensure that it meets their expectations.

- Regression Testing:

Regression testing is performed after changes or updates have been made to the application toensure that the existing functionality has not been affected. This type of testing helps to ensure that new features and updates do not cause any issues in the existing codebase.If the regression testing is not done properly when we add any features to the existing website,it may cause errors.

7.4 Testing the Project

- Test Planning:

Before starting the testing process it is necessary for use to make a plan to test the project thoroughly to achieve this the testing plan should include the testing scope, testobjectives, testing strategies, and the testing schedule.

- Functional Testing:

Functional testing ensures that the application is functioning as intended. Test cases shouldbe created to test each functionality of the application, such as

uploading the image for
classification and checking whether the output of the image in the form of eigen image andpercentage of the accuracy are correct or not.

- Usability Testing: -

Usability testing ensures that the application is easy to use and understand. Testers should testthe application's user interface, user experience, and the speed of the output that is generated by the machine learning model after processing.

- Compatibility Testing:

Compatibility testing ensures that the website is working properly on different window sizesand also in the mobile application after the deployment.

- Performance Testing:

Performance testing ensures that the application performs well under different conditions,such as high-resolution images are sent to the machine learning model for classification.

Testers should test the website and machine learning model performance and response timeunder different scenarios where different images are uploaded and also with increased number of facial images in the upload.

- Regression Testing: -

Regression testing ensures that new changes or updates to the application have not affectedexisting functionality. Testers should perform regression testing after each release or update.

8 IMPLEMENTATION

8.1 Implementation of the project

The implementation of the project with python, HTML and CSS involves several steps.

- Project Setup:

This step involves in installing the required dependencies for creating a project that classifiesgender using facial images.

The dependencies required are:

1. NumPy
2. pandas
3. SciPy
4. matplotlib
5. pillow
6. OpenCV-python-headless
7. scikit-learn
8. flask
9. unicorn

- Design and Development:

  After successfully setting up the project environment and installing all the required dependencies that will be required to make the project, we have developed the website, themachine learning model, backend architecture and the functionality. This consists differentwebpages for displaying the functionality of the website and the webpage where the user uploads an image to classify the gender of the facial image present in the image.

- Coding and Testing:

  In this stage the developer implements the code for the machine learning model, Website to upload the image and the flask backend following best practices and best machine learningtechniques that identify the gender of the image and accuracy of the image gender. We have also performed unit tests, integration tests, and end-to-end testing to ensure that the Website and the machine learning model works as expected.

- Deployment:

  After the application is developed completely and then tested for any potential errors in the functionality it is ready to be deployed as a live application where others can use to classifya picture that they want to.

- Maintenance and Support:

  After deployment, the Website and the machine learning model requires maintenance and support. Which typically involves in fixing any potential bugs and updating the machine learning model to improve its performance and improving the latency of the image to be processed by the machine learning model to make the user experience the application without any unwanted delay, which is typically occurred due to the image processing by the machinelearning model to classify the gender.

8.2 Conversion Plan

The conversion plan for Website for Gender Classification from Facial Imagestypically involves the following steps.

- Analysis of Existing Machine learning approaches:

The initial step that involves in the conversion plan is to analyze the existing machine learning approaches that are used to classify the gender of a facial image and then identifying its strengths and weaknesses. This typically includes in evaluating the model based on its accuracy on wide verity of images including images with high resolution and images with low resolution.

- Identification of the best practices to use in machine learning model:

  Once the existing machine learning model and the different approaches are analyzed we must implement any other approach which is better and well performing than the current methodthat is used in the project.

- Selection of the Conversion Approach:

  After identifying the best practices to use in machine learning model for classifying the facial image we must select the conversion approach according to the requirement which consists partial conversion and complete conversion. Partial conversion involves in training the data with the new and improved method and leaving the rest of the project in the current state, while complete conversion involves in re designing the complete project from rebuilding the machine learning model with different and better approach and implementing a better backend framework better handle the incoming traffic to the machine learning model.

- Development and Testing:

  After the conversion approach has been selected the machine learning model and the website for uploading a facial is developed and tested toc check whether the application is working in the way it is intended and then performing better than the older version to justify the conversion as the conversion plan is mainly chosen to improve the functionality and the performance of the application.

- Deployment and Maintenance:

  After the development of the new method which is improved and well performing as compared to the old approach the Website and the machine learning can be deployed directly without any errors as they are already tested for better performance. If after deploying any errors areoccurred can easily be fixed. In any case we want to include any other functionality to the website can be easily done with the partial conversion plan which is previously discussed inthe current chapter "IMPLEMENTATION".

8.2 Post-Implementation and Software Maintenance:

After successfully implementing the gender classification website from facial images, it is required and crucial to perform the post-implementation and software maintenance tasks to ensure the proper continuation of the website backend and the machine learning model.The few tasks that are performed to safely ensure the working of the machine learning model and the website includes:

- Bug Fixing:

  This involves in checking the functionality of each component of the project to ensure the working of the project in various conditions which typically includes the proper scaling of the website on different resolutions of the screens as laptop monitor and android devices to check the adaptability of the webpage where it takes the input and displays the output to the user who is accessing.

- Performance Monitoring and Optimization:

  It is important the performance if the machine learning model on different conditions andimplement required optimizations if needed. This typically involves in optimizing the machine learning model to better perform on the high-resolution images and also ensuringthe machine learning model to properly identify the gender of the face in a image providedwhich is low resolution by properly tuning the parameters of the model to better perform on both the high resolution and low resolution images

- User Feedback on UI and model improvement:
  feedback on UI of the website and the accuracy of the model that is provided by the user can be used to improve and make necessary changes to make it optimize and better perform assome errors can be over seen by the developer in the development phase and also in the conversion phase although these will occur rarely if properly made but, in some cases, it
  may happen when that case occurs, we can use the user feedback to make necessary changes to optimize and improve the performance of the website and asl well as themachine learning model
- Code Refactoring and Optimization:

As the improvements are done based on the industry standards and the availability of new methods in identifying the gender of the images in an efficient way and to ensure the bettermaintenance of the code, the code refactoring and optimization should be done to ensure the performance improvements.

9. PROJECT LEGACY

9.1 Current Status of the project

The status of the webpage for gender classification using facial images is that the project is currently and tested and well optimized and ready to be deployed as a live website for the users to use and test the functionality on different images containing facial images.

9.2 Remaining Areas of concern

There are still some areas of concern where the project must improve which include.

- Scalability: as there is no multi-processing is implemented the project may fail when there are many users who upload the image for classification at the same time.
- Security: The images that are uploaded for classification are not encrypted in the whole process so this a concern for the privacy of the user that is uploading the images.
- Different images identification: As we implemented this model on only the dataset containing the images of human faces if any other images are uploaded the model gives falsepredictions as it doesn't know the image.

9.3 Technical and Managerial lessons learnt.

Throughout the development and implementation of the machine learning model to classify facial images and the website for uploading images and seeing the classification of the image whether it belongs to male or female we have learned following lessons.

- Effective Communication:

Effective communication is crucial for the success of any project. It is important to establish clear lines of communication between team members, stakeholders, and users. This can help ensure that everyone is aligned and working towards the same objectives.

- Agile Methodology:

Agile methodology is a popular approach to software development that emphasizes flexibility and adaptability. It can be particularly effective for projects withrapidly changing requirements. Agile methodology can help keep the project on track and focused on delivering value to users.

- Quality Assurance and Testing:

Quality assurance and testing play a critical role in software development. Rigorous testing can help ensure that the application meets the needs of users and is free of bugs. Quality assurance helps to ensure that the development processis efficient and effective.

- Collaboration and Teamwork:

Collaboration and teamwork are essential for successful software development. By working together, team members can leverage their strengths and expertise to achieve the best possible results. Good collaboration and teamwork can help ensure that the project is completed on time, within budget, and to the satisfaction of all stakeholders.

- Continuous Improvement:

Continuous improvement is important for software development teams. By continuously assessing and improving processes, tools, and methodologies, the team can ensure that they are delivering the best possible outcomes for users. Continuous improvement helps to ensure that the team is constantly learning and growing, and that the project is always moving forward.

10. SYSTEM SNAPSHOTS

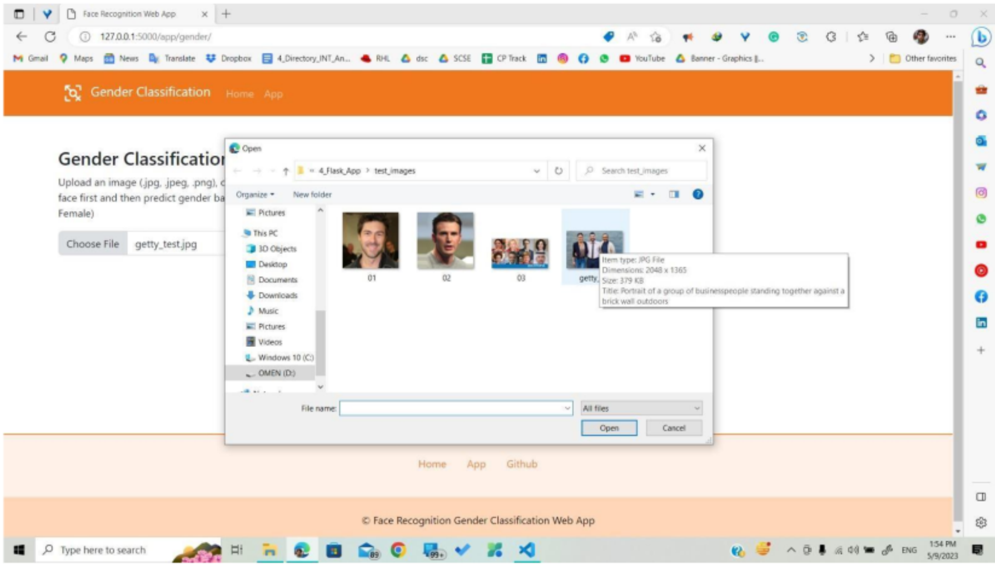

Fig.1 selecting an image to upload to classify the gender of the persons present in theimage.

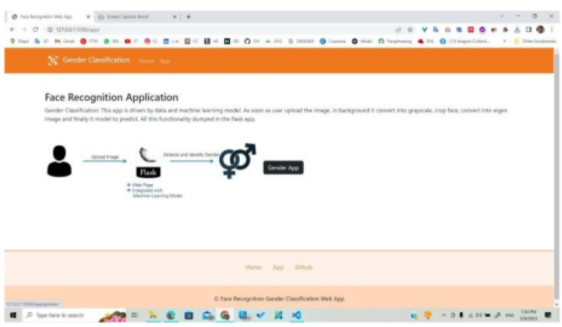

Fig.2 Homepage/Landing page of the website where you can upload the image to classifythe gender.

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