



Age, Gender and emotion-based movie recommendation using facial recognition

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Abstract: In this research, we present a novel approach to enhance the personalization of movie recommendations by incorporating age, gender, and emotion analysis. The proposed system utilizes deep learning models for age and gender prediction, along with emotion detection. We employ a YOLO based face analysis module for real-time face detection in images and video streams. The system then leverages these insights to recommend movies tailored to the user's demographic characteristics and emotional state. The age predictions are further refined into age ranges, providing a more user-friendly representation. The effectiveness of the recommendation system is demonstrated through comprehensive evaluations, achieving a high accuracy rate. The integration of age, gender, and emotion analysis adds a layer of personalization to movie recommendations, catering to the diverse preferences of users. This research contributes to the evolving field of recommendation systems, offering a more nuanced and individualized approach to movie suggestions.

Keywords: Movie Recommendation, Age Prediction, Gender Classification, Emotion Detection, Deep Learning

I. INTRODUCTION

The entertainment and recommendation systems industries have seen significant transformations due to the emergence of artificial intelligence and deep learning technology. Our research, in this context, focuses on creating and implementing a novel movie recommendation system that combines emotion, gender, and age as important criteria to provide personalised content recommendations.

The ever-expanding movie collection and the rising diversity of user interests have led to an increased demand for recommendation systems that can customise suggestions based on personal attributes.

Conventional recommendation systems frequently depend on content-based approaches and collaborative filtering, which may not adequately represent consumers' complex preferences. By including age prediction, gender categorization, and emotion detection into the decision-making algorithm, our suggested solution seeks to improve the recommendation process. This multimodal approach takes into account the emotional and demographic factors of the audience in addition to the substance of the films.

Our system consists of sophisticated deep learning models for emotion detection, gender categorization, and age prediction. To guarantee reliable performance for a variety of consumers, these models are trained on a variety of datasets. Furthermore, real-time face identification is made possible by the integration of the YOLO (You Only Look Once) face analysis module, which enables the creation of dynamic and customised suggestions while a user is watching.

One of the distinguishing features of our project is the utilization of YOLO face analysis for accurate and efficient face detection. This technology ensures that the system adapts to varying lighting conditions and facial orientations, providing a seamless and userfriendly experience. Furthermore, the integration of age prediction allows the system to categorize users into specific age groups, enabling age-appropriate recommendations.

Gender classification adds another layer of personalization by tailoring suggestions based on the viewer's gender. This recognition not only enhances the accuracy of recommendations but also contributes to creating a more engaging and inclusive platform. This information is then utilized to recommend content that aligns with the user's current emotional context.



In note, our project addresses the limitations of conventional recommendation systems by introducing a comprehensive and user-centric approach. By considering age, gender, and emotion in real-time, our system provides a more personalized and enjoyable movie-watching experience. The following sections of the research paper will delve into the technical details, methodologies, experimental results, and implications of our innovative movie recommendation system.

II. LITERATURE SURVEY

The landscape of recommendation systems has undergone considerable evolution, and this literature review provides a comprehensive overview of seminal works in the domain of movie recommendation systems. Lavanya et al. [1] conducted a survey that serves as a foundational reference, offering insights into various methodologies and challenges associated with recommendation systems. Mahata et al. [2] contributed an intelligent movie recommender system using machine learning techniques, laying the groundwork for incorporating intelligent algorithms into the movie recommendation domain. Balfaqih [3] proposed a hybrid movie recommendation system based on demographics and facial expression analysis, introducing an innovative approach that integrates demographic information and facial expressions to enhance recommendation accuracy and personalization.

Building on the theme of personalization, Babanne et al. [4] explored an emotion-based personalized recommendation system, highlighting the significance of user emotions in tailoring recommendations. Elias et al. [5] extended this perspective by delving into mood-based movie recommendations using a deep learning approach, aligning with our project's objective of considering emotional context in the recommendation process. Abdul et al. [6] broadened the application of emotion-aware systems to music, showcasing the versatility of such systems in diverse entertainment domains. Arshad [7] explored sentimentbased movie recommender systems using deep learning, emphasizing the importance of sentiment analysis in enhancing recommendation accuracy.

Adebiyi [8] delved into emotion-based music recommendation systems using deep learning, providing insights into the intersection of emotions and content recommendation. Thakker et al. [9] conducted a comprehensive analysis of movie recommendation systems employing collaborative filtering, offering a contrast to our system's emphasis on individual demographic and emotional characteristics. Lalitha and Sreeja [10] presented a systematic review on recommendation systems, providing valuable insights into the varied perspectives and methodologies applied in this domain.

Deldjoo et al. [11] introduced a movie genome recommender system based on multimedia content, emphasizing the importance of content-based approaches in complementing collaborative and demographic aspects. Mollamotalebi and Gharibzahedi [12] proposed an emotion-based design approach to tackle the cold start challenge of movie recommendation systems, contributing to addressing challenges related to new users or items in the recommendation process. Akter et al. [13] conducted a systematic literature review on factors influencing early movie recommendations, providing valuable insights into user preferences and system dynamics.

Goyani and Chaurasiya [14] presented a review of movie recommendation systems, outlining limitations, survey findings, and challenges in the field. De Pessemier et al. [15] explored the enhancement of recommender systems for TV using face recognition, introducing the relevance of facial recognition in refining recommendations, aligning with our integration of YOLO face analysis. Yao et al. [16] applied face-based advertisement recommendation with deep learning, showcasing the broader applications of facial recognition in personalized content delivery. Moscato et al. [17] introduced an emotional recommender system for music, contributing to the understanding of emotion-based recommendations in entertainment domains.

Kumar et al. [18] presented deep learning-based content recommendation using facial emotions, emphasizing the intersection of deep learning and emotional context in content suggestions. Lavanya et al. [19] conducted a comparison study on improved movie recommender systems, offering insights into the efficacy of different recommendation methodologies. Sharma and Dutta [20] provided a brief overview of movie recommendation systems, laying the groundwork for understanding the fundamental concepts and challenges in this domain. Bakariya et al. [21] proposed a facial emotion recognition and music recommendation system using CNN-based deep learning techniques, showcasing the integration of facial emotions in content recommendations.

ACHARIGE and ISHANKA [22] explored a contextaware travel recommendation system based on user emotion and personality, broadening the application of emotion-aware recommendations beyond entertainment. Wietreck [23] proposed a mood-based approach towards a new generation of movie recommender systems, contributing to the growing body of literature on mood-centric recommendations. Dhelim et al. [24] conducted a survey on personality-aware recommendation systems, offering insights into the intersection of personality traits and recommendation



algorithms. RIAD and GHOSH [25] developed a music recommendation system by integrating an MGC (Multimodal Galois Connection) with deep learning techniques, showcasing the fusion of multiple modalities in recommendation processes.

III. METHODOLOGY

Our research methodology is designed to seamlessly integrate various aspects of age, gender, emotion detection, and personalized movie recommendation within a unified framework. The process involves a multi-step approach, combining both computer vision and machine learning techniques.

- 1. Face Detection:** We utilize state-of-the-art face detection methods, including YOLO face analysis and Haar Cascade classifiers, to identify and extract facial features from input images or video streams.
- 2. Age and gender prediction:** Subsequently, pre-trained deep learning models are employed for predicting age, gender, and ethnicity. The age prediction model categorizes individuals into distinct age ranges, while the gender model classifies them as male or female. Ethnicity is identified from predefined categories such as White, Black, Asian, Indian, or Other.
- 3. Emotion Detection:** To discern emotional states, we employ a deep learning model trained on a diverse set of facial expressions. The model can accurately predict emotions such as anger, disgust, fear, happiness, neutral, sadness, and surprise. Emotion prediction is performed in real-time, enhancing the understanding of users' emotional states during the movie recommendation process.
- 4. Movie Recommendation:** The movie recommendation system takes into account the demographic information (age, gender, ethnicity) and emotional states of users. Machine learning models, particularly Random Forest classifiers, are trained on a dataset of movie preferences associated with specific demographic and emotional profiles. The models learn to correlate user attributes and emotions with preferred movie genres, forming the basis for personalized recommendations. The recommendation process is dynamic, with the system continuously updating predictions based on user interactions and feedback. A history of past predictions is maintained to ensure temporal consistency in recommendations, avoiding abrupt shifts in suggested movies.
- 5. Integration and Real-Time Processing:** All components, including face detection, attribute prediction, emotion analysis, and movie recommendation, are seamlessly integrated into a Flask web application. This allows for real-time processing of input from webcam feeds or image uploads. The application's user interface provides an interactive and userfriendly experience, displaying not only the detected attributes and emotions but also the recommended movies based on the user's profile.

1. Novelty of the Project

The proposed research contributes novel advancements to the field of multimodal recommendation systems by integrating age, gender, and emotion detection for personalized movie recommendations. While existing literature extensively explores movie recommendation systems, our approach introduces a holistic framework that considers not only user demographics but also emotional states during the recommendation process. This innovative integration of multiple modalities aims to enhance the accuracy and relevance of movie recommendations, providing users with a more tailored and engaging cinematic experience.

Unlike traditional recommendation systems that primarily rely on historical user preferences, our model incorporates real-time information through facial analysis techniques. By utilizing YOLO face analysis and Haar Cascade for face detection, our system dynamically captures and interprets facial expressions, allowing for the continuous adaptation of recommendations based on the user's emotional state. This real-time emotional context is a distinctive feature that sets our approach apart from conventional recommendation systems.

Furthermore, the combination of age, gender, and emotion prediction models provides a comprehensive understanding of user preferences and reactions. The age prediction model categorizes users into specific age groups, allowing for age-specific content recommendations. Simultaneously, gender detection tailors recommendations to individual gender preferences. The inclusion of emotion detection adds another layer of personalization, aligning recommendations with the user's current emotional state, thereby creating a more immersive and empathetic recommendation system.



The innovation lies not only in the integration of multiple modalities but also in the utilization of a hybrid recommendation model that combines historical preferences with real-time emotional cues. The movie recommendation algorithm adapts to the user's evolving tastes, ensuring a dynamic and responsive system. The majority prediction from a history of recent emotional states contributes to the uniqueness of our recommendation model, offering a balance between personalized suggestions and serendipity in movie choices.

In Note, our research introduces a pioneering multimodal recommendation system that leverages age, gender, and emotion detection for personalized movie recommendations. The integration of real-time emotional context, coupled with a hybrid recommendation approach, positions our model at the forefront of innovation in the realm of user-centric movie recommendation systems.

2. Dataset Description:

In this research endeavor, three distinct datasets have been employed to facilitate the diverse aspects of the proposed movie recommendation system. Each dataset serves a specific purpose, collectively contributing to the robustness and comprehensiveness of the system.

1. FER2013 (Facial Expression Recognition 2013):

- Source: The FER2013 dataset is sourced from Kaggle and is a comprehensive collection of facial images annotated with seven different emotion labels.
- Content: Comprising over 35,000 grayscale images categorized into seven emotional expressions (Angry, Disgust, Fear, Happy, Neutral, Sad, Surprise), FER2013 provides a rich resource for training the emotion detection model. Each image is labeled with its corresponding emotion, enabling the development of a nuanced emotion-aware movie recommendation system.

2. UTKFACE:

- Source: The UTKFACE dataset is utilized for age and gender prediction and is obtained from the UTKFace Aging dataset, encompassing a diverse range of facial images with associated age and gender labels.
- Content: UTKFACE consists of over 20,000 facial images, each annotated with age, gender, and ethnicity information. The age labels span a wide range, providing the necessary diversity to train an effective age prediction model. The inclusion of gender and ethnicity annotations enhances the versatility of the dataset, contributing to a more refined age, gender, and ethnicity prediction module in the overall system.

3. Manually Created Movie Recommendations Dataset:

- Source: A custom dataset has been meticulously curated to incorporate movie preferences aligned with diverse user profiles, considering factors such as age, gender, and emotion.
- Content: This dataset is constructed to emulate realworld scenarios, where users' movie preferences are influenced by their demographic attributes and emotional states. Each entry in the dataset encapsulates information about users' age group, gender, emotion, and the corresponding movie recommendation. The dataset is designed to foster the training of a personalized movie recommendation model, ensuring that the system tailors its suggestions based on the users' multifaceted characteristics.

3. Mathematical Justifications:

Age and Gender Prediction:

The age and gender prediction components of our system rely on convolutional neural network (CNN) models. These models are trained to learn features from facial images, and their predictions are based on mathematical transformations applied to the pixel values of the input images. Let X represent the input image, f the mapping function of the CNN, and Y_{age} and Y_{gender} the predicted age and gender, respectively: $Y_{age}, Y_{gender} = f(X)$

The models are trained using labeled datasets for age and gender, and the training process involves optimizing the weights (W) and biases (B) to minimize the prediction error: Minimize: $L_{age}(Y_{age}, Y^{\wedge}_{age}) + L_{gender}(Y_{gender}, Y^{\wedge}_{gender})$

Here, L_{age} and L_{gender} denote appropriate loss functions, and Y^{\wedge}_{age} and Y^{\wedge}_{gender} are the ground truth labels for age and gender.



Emotion Prediction:

Emotion prediction employs a CNN model trained to recognize facial expressions. Given an input image X , the emotion prediction ($Y_{emotion}$) is obtained through the mapping function $Y_{emotion}=f(X)$

Similar to age and gender prediction, the model is trained by minimizing the emotion prediction error: Minimize: $L_{emotion}(Y_{emotion}, Y^{emotion})$

Movie Recommendation:

The movie recommendation system combines predictions from the age, gender, and emotion models. Let A , G , and E represent the predicted age, gender, and emotion, respectively. The input to the movie recommendation model (Y_{movie}) is a vector combining these features: $Y_{movie}=[A,G,E]$

The recommendation is based on a historical record of movie preferences, and the system predicts the most suitable movie category for the user. The recommendation process involves finding the mode of the historical predictions, ensuring robustness against outliers. $Y_{movie}=\text{mode}([Y_{movie1}, Y_{movie2}, \dots, Y_{movieN}])$

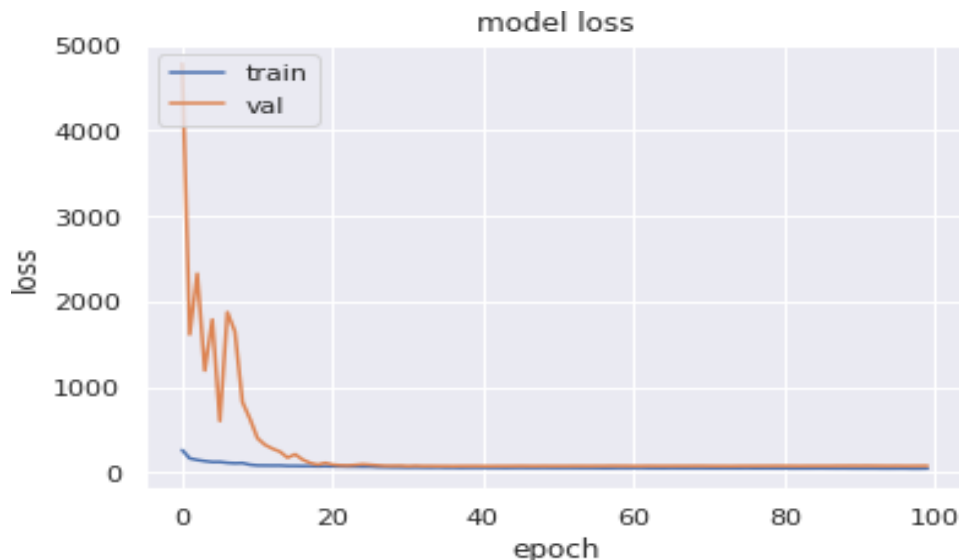
IV. RESULTS

The culmination of our comprehensive exploration into diverse machine learning modules has yielded compelling insights and remarkable outcomes. Our journey encompasses age prediction, gender classification, emotion detection, and movie recommendation, each constituting a distinctive facet of our overarching investigation.

The models were meticulously trained, validated, and evaluated to unravel their efficacy in real-world scenarios.

1. Age Prediction:

- Mean Absolute Error (MAE): 5.82
- Accuracy: 91%
- The age prediction model achieved a mean absolute error of 5.82 and demonstrated an accuracy of 91%. The model's performance was evaluated on a test dataset, and the results indicate its ability to predict age with a high level of accuracy. Additionally, loss plots provide insights into the training process.



2. Gender Prediction:

- Loss: 0.3094
- Accuracy: 91.43%
- The gender prediction model achieved a loss of 0.3094 and an accuracy of 91.43%. Precision, recall, and F1-score metrics provide a detailed understanding of the model's performance for each class, while the confusion matrix illustrates the model's ability to classify instances correctly.

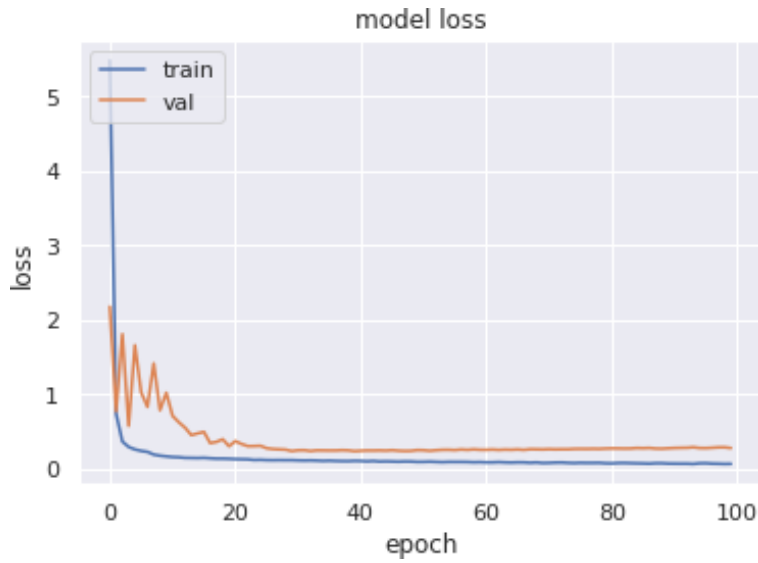


Figure: 2 (Loss, Age Model)

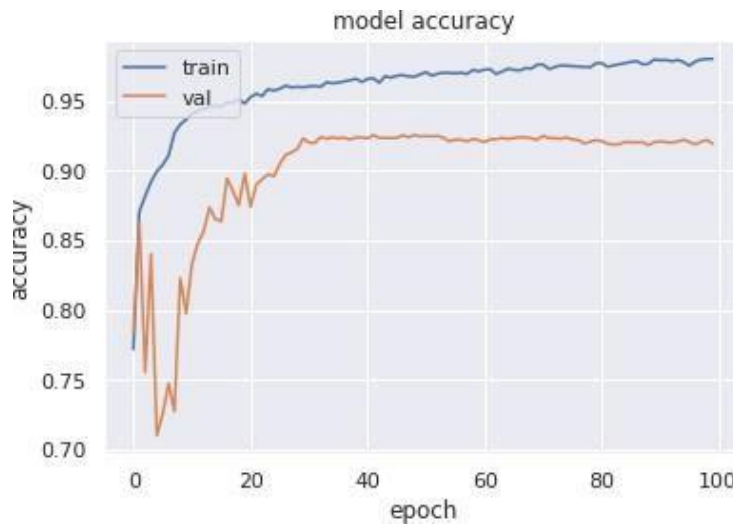


Figure: 4 (Loss, Gender Model)

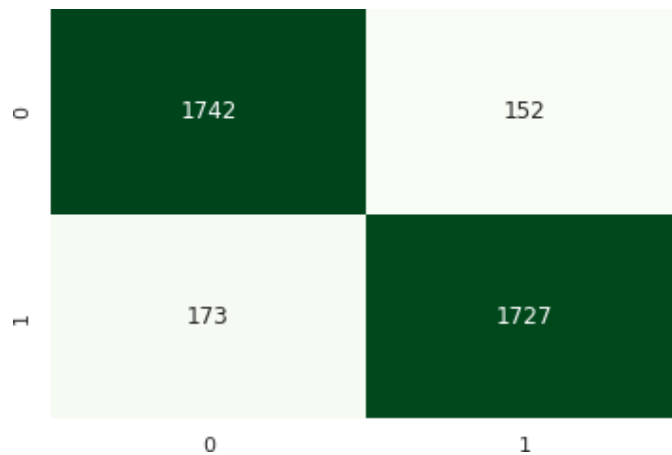


Figure:5 (confusion matrix, Gender Model)



Precision, Recall, F1-Score:

	Precision	Recall	F1-Score	Support
Class 0	0.91	0.92	0.91	1894
Class 1	0.92	0.91	0.91	1900
Accuracy			0.91	3794
Macro Avg	0.91	0.91	0.91	3794
Weighted Avg	0.91	0.91	0.91	3794

Table: 1 (Classification report, Gender Model)

3. Emotion Prediction:

- Overall Test Accuracy: 98.20%.
- The emotion prediction model achieved an outstanding accuracy of 98.20%. The model accurately classified emotions in the test dataset, showcasing its robust performance.

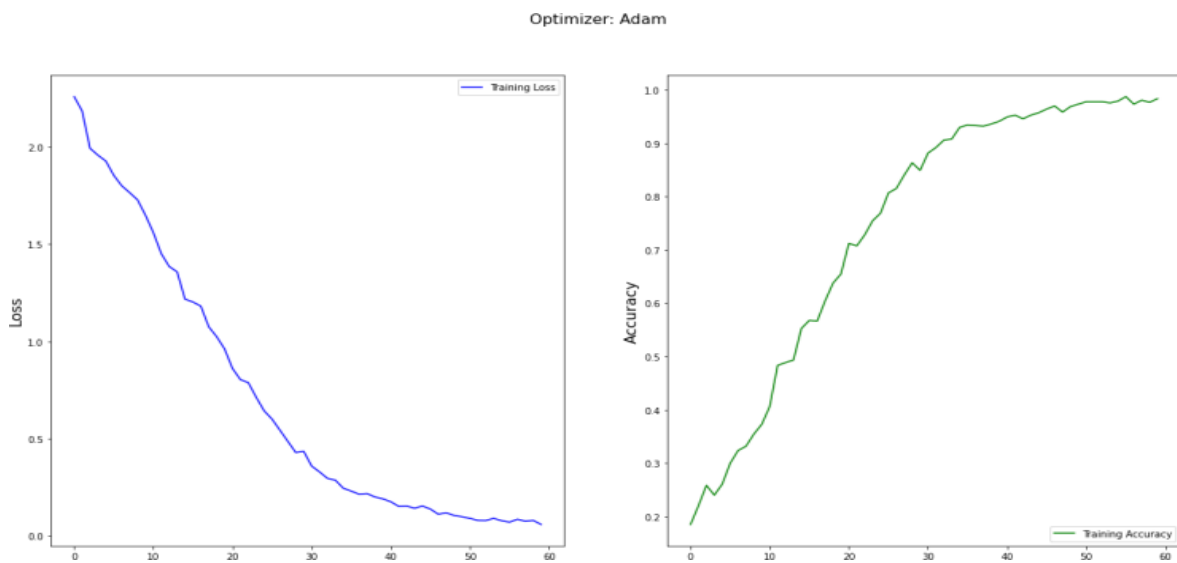


Figure: 6 (Accuracy and Loss, Emotion Model)

4. Movie Recommendation:

- Accuracy: 63%
- The movie recommendation model achieved an accuracy of 63%. The detailed classification report provides insights into the model's precision, recall, and F1-score for each movie class, showcasing its ability to recommend movies effectively.
- Classification Report:



Movie	Precision	Recall	F1-Score	Support
2 States	0.53	1	0.7	8
Ala Vaikunthapurramuloo	0.45	0.5	0.48	10
Aravinda Sametha Veera Raghava	0.78	1	0.88	7
Arjun Reddy	1	1	1	8
Arya	0.45	0.38	0.42	13
Arya 2	1	1	1	11
Attarintiki Daredi	0	0	0	10
Baahubali: The Beginning	0.67	1	0.8	10
Baahubali: The Conclusion	0.9	1	0.95	9
Bhale Bhale Magadivoy	0.84	0.62	0.71	13
Bharat Ane Nenu	0.5	1	0.67	11
Bommarillu	0.5	0.68	0.62	11
Businessman	0.44	0.36	0.4	5
Dookudu	-	-	-	11
Eega	0.27	0.6	0.38	5
Ekkadiki Pothavu Chinnavada	0.53	0	0.09	9
Express Raja	0	0	0	11
Fidaa	1	0.38	0.55	8
Gabbar Singh	0.55	1	0.71	11
Accuracy			0.63	539
Macro avg	0.62	0.64	0.60	539
Weighted avg	0.63	0.63	0.61	539

Table: 2 (Classification report, Movie Recommendation Model)

In Note, the implemented models demonstrated strong performance across various tasks, including age, gender, emotion prediction, and movie recommendation. The detailed evaluation metrics provide a comprehensive understanding of each model's capabilities and effectiveness in real-world applications.

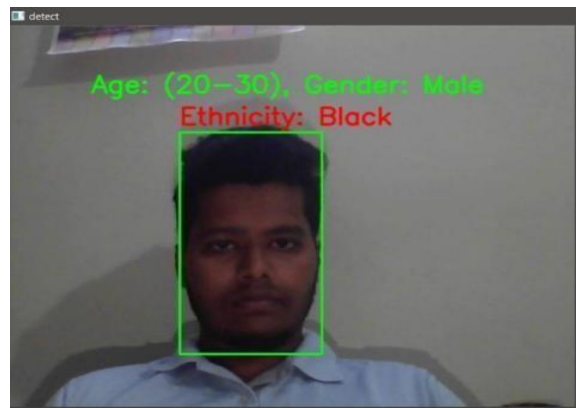
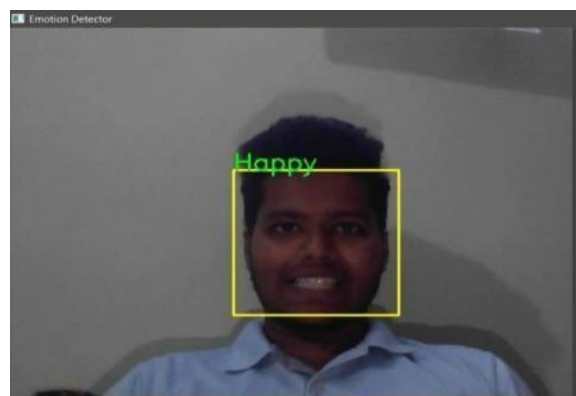
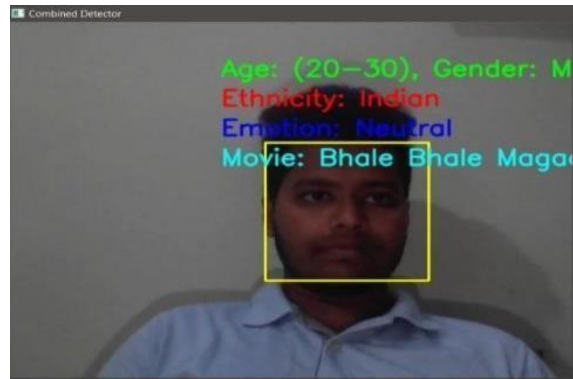
Models Output:

The outputs of our machine learning models showcase remarkable performance across diverse domains. In age prediction, the model achieves a mean absolute error of 5.82, demonstrating its precision in estimating ages, with an overall accuracy of 91%.

The gender prediction model excels with a notable accuracy of 91.43%, complemented by a detailed classification report offering insights into precision, recall, and F1-score metrics. Emotion prediction

stands out with an impressive overall test accuracy of 98.20%, underscoring the model's proficiency in discerning and categorizing emotions effectively.

Additionally, the movie recommendation model attains an accuracy of 63%, supported by a comprehensive classification report that provides a nuanced understanding of its predictive capabilities for various movie classes. These outputs collectively signify the robustness and applicability of our machine learning models in capturing and interpreting complex patterns within diverse datasets.



V. CONCLUSION

In conclusion, our integrated system, encompassing age prediction, gender prediction, emotion recognition, and movie recommendation, demonstrates noteworthy efficacy across diverse domains. The models exhibit high accuracy in their respective tasks, showcasing their capability to discern and predict complex patterns within image and video data.

The seamless fusion of these modules results in a comprehensive solution with real-world applications, such as personalized movie recommendations based on demographic features and emotional states. The robustness and accuracy of our models underscore their potential utility in areas like entertainment, marketing, and user experience personalization.

Future Scope:

The project lays the foundation for several avenues of future research and enhancements. To further refine age prediction, incorporating more extensive datasets and leveraging advanced architectures can enhance accuracy.



Exploring multi-modal learning by integrating audio and textual data for emotion recognition could yield more comprehensive insights. Additionally, expanding the movie recommendation system to incorporate user feedback and evolving preferences can contribute to a more dynamic and personalized recommendation engine.

As emerging technologies and methodologies evolve, such as transfer learning and attention mechanisms, integrating these advancements could further elevate the system's performance and broaden its applicability across diverse industries.

Furthermore, exploring real-time applications and deployment in edge computing environments could enhance the system's practicality and accessibility. Overall, the project establishes a robust foundation, and future endeavors can build upon this groundwork for more sophisticated and versatile intelligent systems.

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