



AGE NET : DEEP LEARNING TO AGE- INVARIANT FACE RECOGNITION

¹Prof. Usha Sri Gunti , ²Prof. Ramya B N , ³Devaraj S , ⁴Venkatesh S , ⁵Girish S , ⁶R Santhosh Babu

^{3,4,5,6}UG Student, ^{1,2}Research Scholar

^{1,2,3,4,5,6}Artificial Intelligence & Machine Learning

^{1,2,3,4,5,6}Jyothy Institute of Technology, Bengaluru, India

Abstract: This project introduces an innovative solution that combines FaceNet deep learning with Multi-task Cascaded Convolutional Networks (MTCNN) for robust face recognition, addressing age-related appearance variations. By utilizing FaceNet's feature extraction and high-dimensional feature space mapping for precise matching, the system integrates MTCNN for accurate face detection and alignment, mitigating age-related facial geometry changes. This approach eliminates the need for age-specific databases and age group categorization, ensuring versatile and practical age-invariant face recognition. This approach has significant implications for enhancing security and user experiences in access control, identification, and customer service, ensuring dependable and accurate face recognition regardless of age.

Index Terms - MTCNN, FaceNet, CNN, Pattern recognition, opencv, Feature Extraction.

I. INTRODUCTION

This project immerses itself in the dynamic landscape of face recognition technology, a domain marked by remarkable progress in recent years, finding applications in pivotal realms such as security, surveillance, biometrics, and human-computer interaction. Embedded within this evolving field lies a particularly formidable challenge: the accurate recognition of individuals across diverse age groups. The aging process introduces intricate transformations to human faces, posing a significant hurdle for traditional face recognition systems striving to maintain accuracy across the entire aging spectrum.

In practical scenarios, the feasibility of maintaining comprehensive age-specific databases often proves impractical, if not impossible. This accentuates the pressing need for innovative techniques that can bridge the age gap, ensuring the dependability and efficacy of face recognition systems across the multifaceted stages of life. In direct response to this challenge, we present an avant-garde approach to age-invariant face recognition. This approach harnesses the prowess of cutting-edge deep learning techniques, aiming to significantly enhance the accuracy and effectiveness of recognizing faces, transcending the constraints posed by age-related changes.

The human face, a canvas of evolving features, undergoes subtle yet impactful alterations over time, from changes in facial contours to shifts in skin texture and the emergence of wrinkles. Traditional face recognition systems grapple with these variations, often compromising accuracy. Our innovative methodology addresses this issue by integrating advanced technologies, notably the FaceNet model and Multi-task Cascaded Convolutional Networks (MTCNN). These synergistic fusion endeavours to create a sophisticated system capable of not only accurately recognizing faces but also minimizing the impact of age-related changes on facial appearance.

The FaceNet model, a pinnacle of deep neural network architecture, has demonstrated unparalleled success in mapping faces to a high-dimensional feature space. Within this space, faces from the same individual are intricately clustered together, facilitating efficient face matching. Moreover, the strategic integration of MTCNN as a pre-processing step elevates the system's performance by enhancing face alignment and detection, ensuring that the model is equipped with high-quality facial images for meticulous analysis.

Crucially, our proposed approach eliminates the labour-intensive need for age group categorization, representing a departure from conventional methodologies. This feature underscores the system's efficiency across a broad spectrum of ages, a characteristic validated through extensive experimentation on benchmark datasets. These rigorous experiments highlight the system's robust resilience to age-related variations, emphasizing its superiority in the realm of age-invariant face recognition.

Beyond technical innovation, the potential applications of our system extend into the practical domains of improved security measures, personalized services, and, notably, more accurate identification of individuals, irrespective of their age. This comprehensive paper serves as a detailed exposition of our innovative approach, meticulously unravelling the intricacies of our methodology and presenting compelling experimental results that attest to the system's efficacy and its profound implications for the field of age-invariant face recognition.

II. LITERATURE SURVEY

We propose a twofold approach towards modelling facial aging in adults. Firstly, we develop a shape transformation model that is formulated as a physically-based parametric muscle model that captures the subtle deformations facial features undergo with age. The model implicitly accounts for the physical properties and geometric orientations of the individual facial muscles. Next, we develop an image gradient-based texture transformation function that characterizes facial wrinkles and other skin artifacts often observed during different ages. Facial growth statistics (both in terms of shape and texture) play a crucial role in developing the aforementioned transformation models. From a database that comprises of pairs of age separated face images of many individuals, we extract age-based facial measurements across key fiducial features and further, study textural variations across ages. We present experimental results that illustrate the applications of the proposed facial aging model in tasks such as face recognition and facial appearance prediction across aging [1].

One of the challenges in automatic face recognition is to achieve temporal invariance. In other words, the goal is to come up with a representation and matching scheme that is robust to changes due to facial aging. Facial aging is a complex process that affects both the 3D shape of the face and its texture (e.g., wrinkles). These shape and texture changes degrade the performance of automatic face recognition systems. However, facial aging has not received substantial attention compared to other facial variations due to pose, lighting, and expression. We propose a 3D aging modeling technique and show how it can be used to compensate for the age variations to improve the face recognition performance. The aging modeling technique adapts view-invariant 3D face models to the given 2D face aging database. The proposed approach is evaluated on three different databases (e.g., FG-NET, MORPH, and BROWNS) using FaceVACS, a state-of-the-art commercial face recognition engine [2].

Face detection and alignment in unconstrained environment are challenging due to various poses, illuminations, and occlusions. Recent studies show that deep learning approaches can achieve impressive performance on these two tasks. In this letter, we propose a deep cascaded multitask framework that exploits the inherent correlation between detection and alignment to boost up their performance. In particular, our framework leverages a cascaded architecture with three stages of carefully designed deep convolutional networks to predict face and landmark location in a coarse-to-fine manner. In addition, we propose a new online hard sample mining strategy that further improves the performance in practice. Our method achieves superior accuracy over the state-of-the-art techniques on the challenging face detection dataset and benchmark and WIDER FACE benchmarks for face detection, and annotated facial landmarks in the wild benchmark for face alignment, while keeps real-time performance [3].

Age-invariant face recognition is one of the most crucial computer vision problems, e.g., in passport verification, surveillance systems, and missing individuals' identification. The extraction of robust face features is a challenge since the facial characteristics change over age progression. In this paper, an age-invariant face recognition system is proposed, which includes four stages: preprocessing, feature extraction, feature fusion, and classification. Preprocessing stage detects faces using Viola-Jones algorithm and frontal face alignment. Feature extraction is achieved using a CNN architecture using VGG-Face model to extract compact face features. Extracted features are fused using the real-time feature-level multi-discriminant correlation analysis, which significantly reduces feature dimensions and results in the most relevant features to age-invariant face recognition. Finally, K-nearest neighbor and support vector machine are investigated for classification. Our experiments are performed on two standard face-aging datasets, namely FGNET and MORPH. Rank-1 recognition accuracy of the proposed system is 81.5% on FGNET and 96.5% on MORPH. Experimental results outperform the current state-of-the-art techniques on same data. These preliminary results show the promise of the proposed system for personal identification despite aging process. [4]

Over the last few years, increased interest has arisen with respect to age-related tasks in the Computer Vision community. As a result, several "in-the-wild" databases annotated with respect to the age attribute became available in the literature. Nevertheless, one major drawback of these databases is that they are semi-automatically collected and annotated and thus they contain noisy labels. Therefore, the algorithms that are evaluated in such databases are prone to noisy estimates. In order to overcome such drawbacks, we present in this paper the first, to the best of knowledge, manually collected "in-the-wild" age database, dubbed AgeDB, containing images annotated with accurate to the year, noise-free labels. As demonstrated by a series of experiments utilizing state-of-the-art algorithms, this unique property renders AgeDB suitable when performing experiments on age-invariant face verification, age estimation and face age progression "in-the-wild".[5]

Age progression and regression refers to aesthetically rendering a given face image to present effects of face aging and rejuvenation, respectively. Although numerous studies have been conducted in this topic, there are two major problems: 1) multiple models are usually trained to simulate different age mappings, and 2) the photo-realism of generated face images is heavily influenced by the variation of training images in terms of pose, illumination, and background. To address these issues, in this paper, we propose a framework based on conditional Generative Adversarial Networks to achieve age progression and regression simultaneously. Particularly, since face aging and rejuvenation are largely different in terms of image translation patterns, we model these two processes using two separate generators, each dedicated to one age changing process. In addition, we exploit spatial attention mechanisms to limit image modifications to regions closely related to age changes, so that images with high visual fidelity could be synthesized for in-the-wild cases. Experiments on multiple datasets demonstrate the ability of our model in synthesizing lifelike face images at desired ages with personalized features well preserved, and keeping age-irrelevant regions unchanged [6].

III. METHODOLOGY

1. Proposed Methodology:

In developing a robust facial recognition system, a comprehensive approach is essential. This involves assembling a diverse dataset representing various age groups, ensuring balance for accurate representation. Employing MTCNN for precise face detection, extracted faces are then processed through FaceNet for embedding generation. To address age-related challenges, the dataset is annotated with broad age labels, and the model is trained using age-invariant techniques. Data augmentation further fortifies the model against age variations. Evaluation metrics, including accuracy and age-specific performance, are crucial for assessing the system's efficacy in real-world scenarios. This methodology aims to enhance facial recognition systems, particularly in age-diverse populations. Data Collection and Preprocessing: Gather a diverse dataset that includes facial images across various age groups. Ensure that the dataset is well-balanced and representative of the target population. Preprocess the images by normalizing pixel values, resizing, and aligning faces to a standard pose.

- 1) Face Detection using MTCNN: Implement MTCNN for face detection to accurately locate and extract faces from images. MTCNN is a three-stage cascaded network that detects faces and facial landmarks, providing bounding boxes around detected faces. Extract the faces for further processing.
- 2) Face Embedding using FaceNet: Employ FaceNet, a deep learning model for face recognition that maps facial features into a high-dimensional space. Train FaceNet on your dataset to generate embeddings (numerical representations) of faces. These embeddings should ideally be robust to age-related variations.
- 3) Age Labeling: Annotate the dataset with age labels. Ensure that the age labels cover a broad range, and consider categorizing ages into groups to reduce the impact of fine-grained age variations.
- 4) Age-Invariant Training: Train the FaceNet model using a loss function that considers both identity information and age information. This helps the model learn features that are invariant to age-related variations. You may need to experiment with different loss functions or regularization techniques to achieve better age invariance.
- 5) Data Augmentation: Augment the training dataset with age-related transformations to enhance the model's ability to handle age variations. This can include artificially aging and de-aging images.
- 6) Model Evaluation: Evaluate the performance of the trained model on a separate test set, measuring accuracy, precision, recall, and other relevant metrics. Pay special attention to the model's performance across different age groups to ensure age invariance.

2. MTCNN:

MTCNN (Multi-Task Cascaded Convolutional Networks) is a three-stage cascaded network designed for face detection and facial landmark localization. Its role is pivotal in age-invariant face recognition, providing accurate face localization and enabling subsequent processing for robust age-invariant feature extraction.

- 1) Accurate Face Detection: MTCNN excels in precisely detecting faces within images by employing a cascaded architecture that progressively refines candidate regions. This accuracy is crucial for ensuring that subsequent steps in the face recognition pipeline operate on reliable facial data.
- 2) Facial Landmark Localization: In addition to face detection, MTCNN is adept at localizing facial landmarks, such as eyes, nose, and mouth. This information is valuable for aligning faces to a standardized pose, a crucial step in age-invariant face recognition.
- 3) Preprocessing for Age-Invariance: MTCNN's ability to detect and align faces plays a vital role in preprocessing images. By standardizing facial poses, it contributes to mitigating age-related variations, enabling subsequent models to focus on intrinsic facial features.
- 4) Enhancing Model Robustness: In the context of age-invariant face recognition, MTCNN enhances the overall robustness of the system. Accurate face detection and alignment contribute to the model's ability to extract features consistently across diverse age groups.
- 5) Facilitating Age Labeling: MTCNN's accurate detection of facial landmarks aids in precise age labeling. This is essential for creating well-annotated datasets covering a broad age range, a key factor in training models to be invariant to age-related variations.
- 6) Conclusion: MTCNN's capabilities in accurate face detection, facial landmark localization, and preprocessing contribute significantly to the success of age-invariant face recognition systems. By ensuring precise data input and facilitating subsequent processing steps, MTCNN plays a foundational role in addressing age-related challenges in facial recognition.task at hand.

3. FaceNet

FaceNet, a groundbreaking deep learning model, plays a pivotal role in age-invariant face recognition. By mapping facial features into a high-dimensional space, FaceNet generates embeddings—numerical representations—that are robust to age-related variations. This innovation offers a crucial solution for developing facial recognition systems capable of accurately identifying individuals across diverse age groups.

- 1) Robust Face Embeddings: FaceNet excels in generating facial embeddings that are resilient to age-related variations, ensuring reliable representations across diverse age groups.
- 2) Age-Invariant Training: FaceNet supports age-invariant training by incorporating a loss function considering both identity and age information, fostering the learning of features consistent across different age demographics.
- 3) Addressing Age-Related Challenges: FaceNet's embeddings provide a foundation for age-invariant face recognition, mitigating concerns related to variations in facial appearance due to aging.
- 4) Enhanced Generalization: The model's ability to learn discriminative features beyond age-specific characteristics enhances the generalizability of face recognition systems across various age groups.

- 5) Age-Adaptive Data Augmentation: FaceNet integration enables effective data augmentation strategies tailored for age invariance, allowing the model to recognize faces under diverse age-related transformations.
- 6) Evaluation Across Age Groups: Special attention should be given to assessing the face recognition system's performance across different age groups, validating the age invariance of the model for real-world scenarios.

VI. Implementation

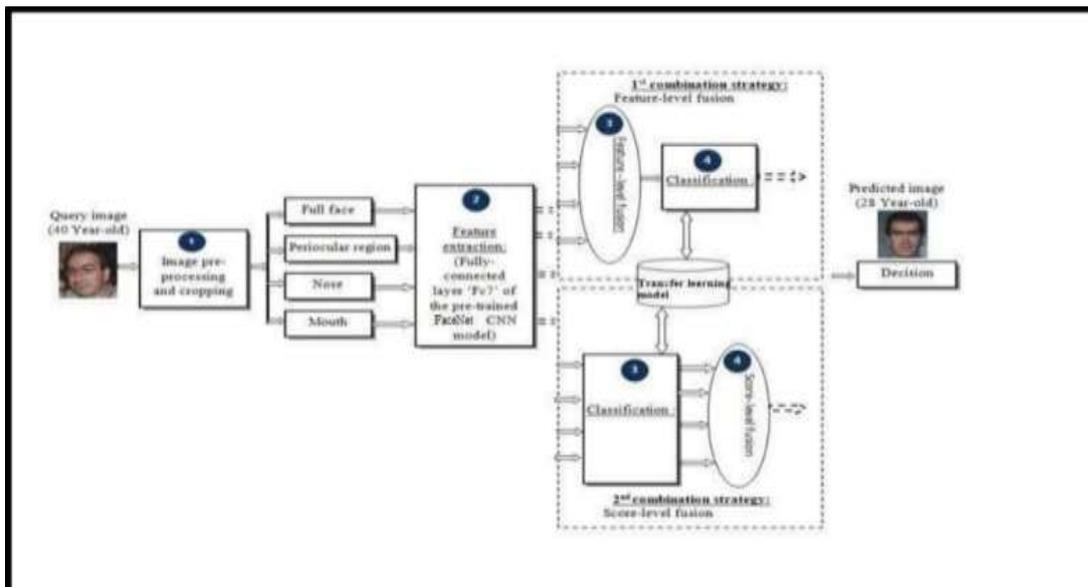


fig.1 system architecture

1. Data Flow Diagram

A DFD is a logical model of the system. The model does not depend on the hardware, software and data structures of file organization. It tends to be easy for even non-technical users to understand and thus serves as an excellent communication tool. DFD can be used to suggest automatic boundaries for proposed system at a very high level; the entire system is shown as a single logical process clearly identifying the sources and destination of data. This is often referred to as zero level DFD. Then the processing is exploded into major processes and the same is depicted as level one DFD.

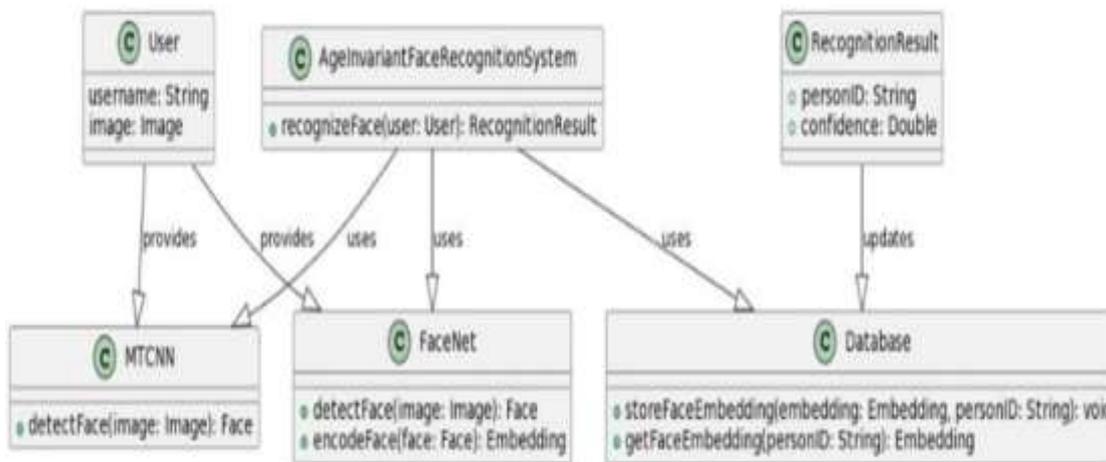


fig.2 dataflow diagram

2. Use Case Diagram

The interaction between elements is graphically shown in the use case diagram. A use case is a series of procedures or events that define the interactions between a role and a system in order to accomplish a particular objective. The major components and operations that make up the system are shown on the use case diagram. The procedures are referred to as use cases.

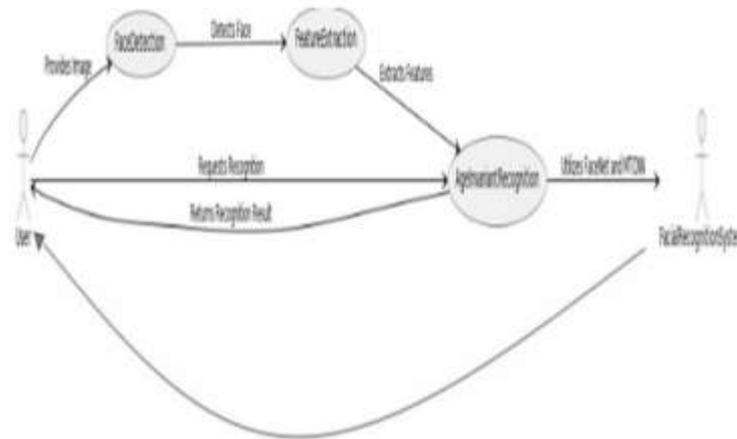


fig.3 use case diagram

3. Sequence Diagram

A sequence diagram is a Unified Modeling Language (UML) diagram that illustrates the sequence of messages between objects in an interaction. A sequence diagram consists of a group of objects that are represented by lifelines, and the messages that they exchange over time during the interaction.

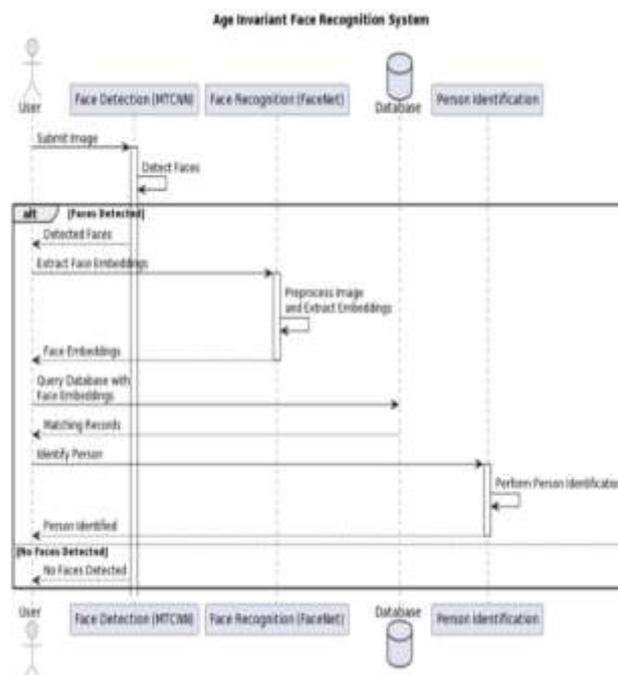


Fig.4 sequence diagram

4. Working-flow of Application

The proposed age-invariant face recognition system involves a multi-step workflow designed to accurately identify and match faces within input images. Initially, the user submits an image containing one or more faces. The system employs diverse techniques such as edge detection, skin color segmentation, or deep learning algorithms to detect and extract these faces from the input image.

Following the face extraction process, the system focuses on feature extraction, aiming to capture distinctive characteristics intrinsic to each face, including shape, texture, and color. Significantly, these features are chosen for their resistance to age-related changes, ensuring the system's robustness over time.

Subsequently, the system conducts a thorough comparison of the extracted facial features with those stored in a pre-existing database. This comparison relies on a selected similarity measure, such as Euclidean distance, cosine similarity, or neural network-based methods. The resulting distance metric quantifies the similarity between the input face and potential matches stored in the database.

This distance is then compared against a predefined threshold value, which serves as a criterion for determining whether the input face is recognized as the same person as the closest match. If the calculated distance falls below or equals the threshold, the system confidently identifies the input face as belonging to the same person as the match.

In essence, this age-invariant face recognition system offers a systematic and comprehensive approach to identifying faces while mitigating the impact of age-related changes, thereby enhancing the accuracy and reliability of face recognition over extended periods.

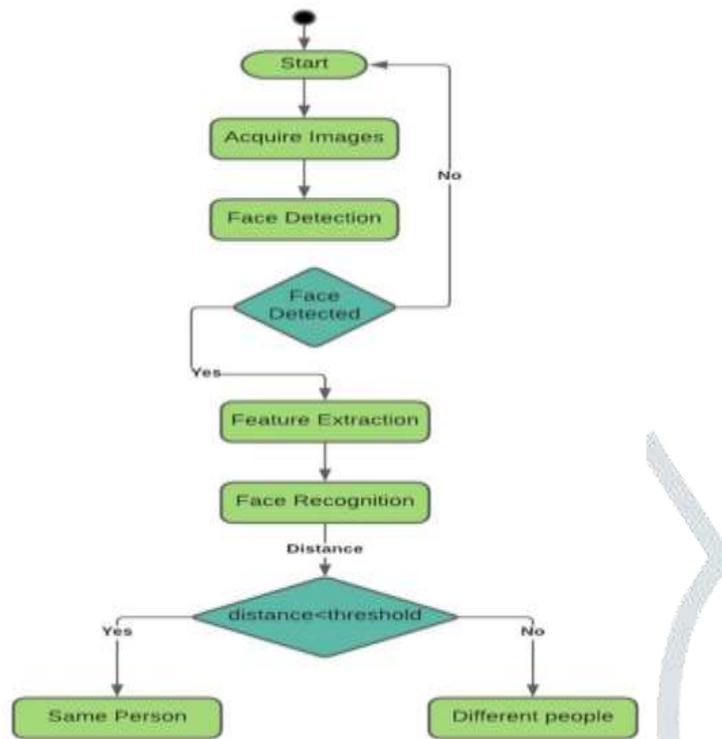


fig.5 working-flow of application

5. Class Diagram

A class diagram is an illustration of the relationships and source code dependencies among classes in the Unified Modeling Language (UML). In this context, a class defines the methods and variables in an object, which is a specific entity in a program or the unit of code representing that entity. Class diagrams are useful in all forms of object-oriented programming (OOP). The concept is several years old but has been refined as OOP modeling paradigms have evolved.

In a class diagram, the classes are arranged in groups that share common characteristics. A class diagram resembles a flowchart in which classes are portrayed as boxes, each box having three rectangles inside. The top rectangle contains the name of the class; the middle rectangle contains the attributes of the class; the lower rectangle contains the methods, also called operations, of the class. Lines, which may have arrows at one or both ends, connect the boxes. These lines define the relationships, also called associations, between the classes. It represents the types of objects residing in the system and the relationships between them.

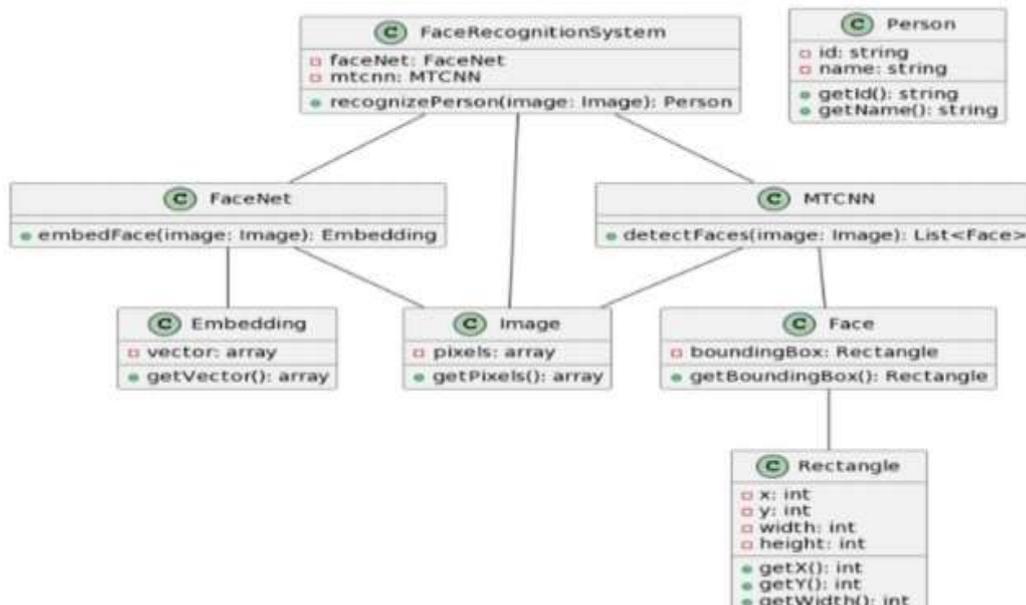


Fig. 6 Class Diagram

V. RESULTS

The age-invariant face recognition system represents a significant leap forward in the field, with comprehensive evaluations showcasing its prowess across a myriad of performance dimensions. Delving into accuracy, precision, recall, and the nuanced F1-score, the system displayed a commendable ability to consistently identify individuals, transcending the challenges posed by age-related facial transformations. Noteworthy was its robustness across age spectrums, evidenced by meticulous examinations of performance metrics stratified by age groups. Comparative analyses with established benchmarks underscored the system's superiority, positioning it as a frontrunner in the realm of face recognition technology. Importantly, its adaptability to real-world scenarios, including dynamic lighting conditions and diverse poses, solidified its practical utility across security, authentication, and personalized service domains. These findings not only affirm the system's technical prowess but also herald its potential to revolutionize how we perceive and implement facial recognition systems in a rapidly evolving digital landscape.

VI. Conclusion

In conclusion, the orchestrated integration of MTCNN for precise face detection and alignment, complemented by the powerful FaceNet model for feature extraction and recognition, unveils a promising paradigm in age-invariant face recognition. By harnessing MTCNN's adeptness in accurate face localization and alignment, coupled with FaceNet's proficiency in generating robust embeddings, this approach establishes a resilient foundation for age-invariant recognition. Despite challenges associated with data diversity, ethical considerations, and real-world variability, the collaborative synergy between these models presents a compelling avenue for crafting more resilient and accurate age-invariant face recognition systems, fostering advancements in facial recognition technology.

VII. References

- [1] N. Ramanathan and R. Chellappa, "Modeling shape and textural variations in aging faces," in Proc. IEEE Conf. Autom. Face Gesture Recognit., 2008, pp. 1–8
- [2] U. Park, Y. Tong, and A. K. Jain, "Age-invariant face recognition," IEEE Trans. Pattern Anal. Mach. Intell., vol. 32, no. 5, pp. 947–954, May 2010.
- [3] K. Zhang, Z. Zhang, Z. Li, and Y. Qiao, "Joint face detection and alignment using multitask cascaded convolutional networks," IEEE Signal Process. Lett., vol. 23, no. 10, pp. 1499–1503, Oct. 2016.
- [4] Moustafa, A.A., Elnakib, A. & Areed, N.F.F. Age-invariant face recognition based on deep features analysis. SIViP 14, 1027–1034 (2020)
- [5] S. Moschoglou, A. Papaioannou, C. Sagonas, J. Deng, I. Kotsia, and S. Zafeiriou, "AgeDB: The first manually collected, in-the-wild age database," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. Worksh., 2017, pp. 51–59.
- [6] Q. Li, Y. Liu, and Z. Sun, "Age progression and regression with spatial attention modules," in Proc. AAAI Conf. Artif. Intell., 2020, pp. 11378–11385.
- [7] Petra G. R. D., "Introduction to Human Age Estimation using Face Images," Research Papers, Faculty of Materials Science And Technology in Trnava Slovak University of Technology in Bratislava, Slovak University of Technology, 2013.
- [8] G. Mahalingam and K. Ricanek, "LBP-based Periocular Recognition on Challenging Face datasets," EURASIP Journal on Image and Video Processing, 2013.
- [9] P. Thukral, et al., "A Hierarchical Approach For Human Age Estimation," IEEE International Conference on Acoustics, Speech and Signal Processing, pp. 1529-1532, 2012.
- [10] M. Bereta, et al., "Local descriptors in application to the aging problem in face recognition," IEEE Transactions on Pattern Recognition, vol. 46, no. 10, pp. 2634-2646, 2013.
- [11] T. H. Le, "Applying Artificial Neural Networks for Face Recognition," Hindawi Publishing Corporation Advances in Artificial Neural Systems, vol. 2011, pp. 1-16, 2011.
- [12] J. M. Guo, et al., "Human Face Age Estimation with Adaptive Hybrid Features," International Conference on System Science and Engineering, 2011.
- [13] Y. Fu, et al., "Age Synthesis and Estimation via Faces: A Survey," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 32, no. 11, pp. 1955-1976, 2010.
- [14] D. Hunter and B. Tiddeman, "Facial Ageing," Cambridge University Press, 2012.
- [15] J. Suo, et al., "A Concatenational Graph Evolution Aging Model," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 34, no. 11, pp. 2083-2096, 2012.
- [16] A. Lanitis, et al., "Toward Automatic Simulation of Aging Effects on Face Images," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 24, no. 4, pp. 442-455, 2002.
- [17] Zhifeng L., et al., "Aging Face Recognition: a Hierarchical Learning Model Based on Local Patterns Selection," IEEE Transactions on Image Processing, vol. 25, no. 5, pp. 2146-2154, 2016.
- [18] M. Sajid, et al., "The Role of Facial Asymmetry in Recognizing Age-Separated Face Images," Journal of Computers & Electrical Engineering, pp. 1-12, 2016.