



# **A Survey on Comprehensible and Multi Feature Based Methodology of Age Prediction Using Neural Network**

*<sup>1</sup>B. Vijaya Kumar, <sup>2</sup>R. Sivaprasad, <sup>3</sup>Agash. V, <sup>4</sup>Vibin Venkatesh. S*

<sup>1</sup>Guide, <sup>2,3,4</sup>Student

<sup>1,2,3,4</sup>Sri Manakula Vinayagar Engineering College

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## **ABSTRACT**

Face-based age estimation has drawn a lot of attention since it has numerous applications in areas including human-computer interaction and public security surveillance. Age estimation based on deep neural networks has become common practise with the rapid development of deep learning. It is still necessary to research a better issue paradigm for age change characteristics, the appropriate loss function, and a more potent feature extraction module. In order to use these semantic features for age estimate, we construct a face parsing-based network to semantic information at various scales and a novel face parsing attention module. We demonstrate that our method continuously beats all age estimation methods and achieves a new state-of-the-art performance through extensive experimentation on dataset. Our work is, to the best of our knowledge, the first effort to use face parsing attention to achieve semantic-aware age prediction, which may serve as an example for other challenging facial analysis problems.

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## **I. INTRODUCTION**

For face alignment, a crucial processing step between face detection and recognition, accurate facial feature extraction is crucial. The goal of this study is to develop a feature-extraction system that may be applied to consumer or embedded applications for face recognition. In addition to extraction accuracy, this places additional demands on the algorithm, such as real-time performance under a variety of imaging situations and robustness with inexpensive imaging gear. The processing of human facial images has long been a topic of active and fascinating research. Since human faces contain so much information, several themes have received a lot of attention and have been the subject of in-depth research. Face recognition is the most popular of them. Additional study topics include recreating faces from a set of predetermined features and predicting feature faces [2].

For an exceptionally social animal like us humans, gender categorization is perhaps one of the more crucial visual skills. Many social interactions heavily rely on the parties' accurate gender perceptions. One of the more significant sources of information for gender classification, in my opinion, is the visual information from human faces. So, it is not unexpected that a huge number of psychophysical research have looked into how humans classify gender based on how they perceive faces. A fascinating problem with various applications in digital entertainment is face ageing simulation and prediction. Personal identity and verification issues are a rapidly expanding field of study. The most popular forms of verification include face, voice, lip movements, hand geometry, odour, stride, iris, retina, and fingerprints

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## **II. LITERATURE SURVEY**

The authors have given a thorough analysis of AI-based FER methodology, including datasets, feature extraction techniques, algorithms, and the most current developments with their applications in facial expression detection, in this literature review. To the best of the authors' knowledge, this is the first review article that covers all FER-related topics for different age groups and will have a big impact on the research community in the years to come.

### **PAPER 1: A DEEP LEARNING MODEL FOR CLASSIFICATION OF AGE AND GENDER FROM FACIAL IMAGES:**

#### **DESCRIPTION:**

Several researchers have studied the issue of gender and age identification, although they have paid far less attention to it than to other related issues, particularly those involving facial recognition. When compared to other facial recognition issues, the success obtained in this sector has not much improved. Every language in the world has its own vocabulary and grammatical conventions for speaking to people of various ages. The choice about its application depends on our capacity to distinguish these specific traits, including gender and age, from the face appearances at a glance. We anticipate such decision-making power with the rising adoption of Artificial Intelligence (AI) based technologies in several domains. In order to achieve this, we developed a deep learning model in this study called Garnet (Gated Residual Attention Network), which enables us to predict age and gender from facial photos. This is a revised and improved version of the Residual Attention Network, whose architecture now incorporates the idea of gates.

Whereas age prediction is a regression problem, gender identification is a binary classification challenge. For greater accuracy, we divided the regression problem into a set of classification and regression questions. Five publicly accessible standard datasets—FG-Net, Wikipedia, AFAD, UTK Face, and Audience DB—have been used in experiments. The obtained results have demonstrated its efficacy for both age and gender classification, making it a legitimate contender for the same versus any other cutting-edge techniques.

#### **PAPER 2: WASSERSTEIN DIVERGENCE GAN WITH CROSS-AGE IDENTITY EXPERT AND ATTRIBUTE RETAINER FOR FACIAL AGE TRANSFORMATION:**

##### **DESCRIPTION:**

For facial age alteration, we recommend the Wasserstein Divergence GAN with an identity specialist and an attribute retainer. Better training stabilisation and improved target picture production are two benefits of using the Wasserstein Divergence GAN (WGAN-div). The identity expert seeks to maintain the output identity,

and the output attribute. Unlike to other efforts, which adopted a specific model for identity and attribute preservation without providing a justification, our suggested model's identity expert and attribute retainer were chosen after an extensive comparison analysis of the most advanced pretrained models. The VGG-Face, VGG-Face2, Light CNN, and Arc Face are some of the potential networks that are being taken into account for identity retention. The VGG-Face, VGG-Object, and DEX networks are prospective backbones for the attribute retention. A selection manual for the best modules for identity and attribute preservation is provided by this study. interactions between identity and attribute experts

Much research and testing have also been done on retainers. We argue the data using the 3DMM and investigate the benefits of extra training on cross-age datasets to further improve performance. It is validated that the additional cross-age training equips the identification expert with the necessary skills to manage cross-age face recognition. The targeted age transition with well-preserved identity justifies the effectiveness of our method. Tests on benchmark databases demonstrate how competitive the suggested approach is with cutting-edge techniques.

#### **PAPER 3: FEATURES, ML & DL TECHNIQUES, AGE WISE DATASETS AND FUTURE DIRECTIONS:**

##### **DESCRIPTION:**

Human emotions and thoughts can be read through facial expressions. It offers the audience a multitude of social clues, such as the attentional focus, goal, motivation, and emotion. It is said to be a strong silent communication tool. Study of these expressions provides a far deeper understanding of human behaviour. With applications in dynamic analysis, pattern identification, interpersonal interaction, mental health monitoring, and many other fields, AI-based facial expression recognition (FER) has emerged in recent years as one of the most important study areas. Yet, there has been a compelling need to innovate and provide a new FER analysis framework with the growing visual data generated by films and images due to the global drive towards online platforms as a result of the Covid-19 pandemic. Also, the emotional expressions that children, adults, and senior citizens make differ, which must also be taken into account in the FER research. This topic has been the subject of extensive inquiry. Unfortunately, a thorough review of the literature that highlights prior research and outlines compatible future approaches is lacking.

#### **PAPER 4: SOFT-RANKING LABEL ENCODING FOR ROBUST FACIAL AGE ESTIMATION:**

##### **DESCRIPTION:**

Many practical applications exist for automatic face age estimate. Due to the randomness and slowness of the ageing process, this process is difficult. As a result, we suggest a novel method in this study that aims to solve the problems with face age estimation. The ordinal property and the connection between neighbouring ages are two crucial characteristics of face age that are encoded via a novel age encoding technique we call Soft-ranking. As a result, Soft ranking offers a richer supervision signal for deep model training. Additionally, we thoroughly examine the assessment protocols currently in use for age estimation and discover that the identity overlap between the training and testing sets has an impact on how well various age encoding techniques perform against one another. Also, in the four most widely used age databases—Morph II, AgeDB, CLAP 2015, and CLAP 2016—we achieve cutting-edge performance.

By contributing in various ways, we hope to address the difficulties in estimating face age in this work. Secondly, a modern encoding technique called Soft-ranking is suggested. The correlation between the current age encoding schemes and the ordinal information are seamlessly combined via soft-ranking. Second, we draw attention to the fact that the identification overlap between. Using training and testing sets together could lead to inaccurate findings when evaluating the age estimate algorithm. On the basis of the suggested methodologies, we achieve cutting-edge findings for four well-known age estimation databases.

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### **III. EXISTING SYSTEM**

Individuals age in various ways. Given that it more accurately mimics the personalization of ageing processes, learning a personalised age estimator for each individual is a promising avenue for age estimation. Hoauthorsver, the high-level requirements—identity labels and enough samples for each person to build a long-term ageing pattern—mean that the majority of personalised approaches currently in use suffer from a shortage of large datasets. The authors of this study suggest a meta-learning technique called Meta Age for age estimation in order to develop tailored age estimators without the aforementioned prerequisites. Instead of directly learning the parameters of estimators, the current method considered learning to learn personalised estimators. Humans have a rapid capacity for skill acquisition and situational adaptation. Authors must learn how to acquire new tasks more quickly if

they want to understand the current AI systems with this capability. In order to learn how to adapt to new tasks, eta-learning systems often use a lot of training tasks. The authors suggest a personalised estimator meta-learner that learns to learn tailored age estimators using the aforementioned tasks. The Meta Age gains information of how identity-related factors affect the parameters of customised estimators throughout the training process. For instance, the Meta Age learns how diverse races affect individualised estimators. The Meta Age must next apply the knowledge it has learnt to a test task. Despite the fact that authors may never see the test subject, they can still learn about the subject's characteristics thanks to the identifying features that were extracted. Based on the information gathered about the qualities, the learnt understanding of how identity-related attributes affect estimators is applied to the particular situation. Our method learns the mapping from identification information to age estimator parameters rather than learning the parameters of an adaptive age estimator for each individual as the most personalised methods did. Our method can use any existing large-scale age estimation datasets without any additional annotations since the suggested Meta Age does not require the age datasets to have identity labels and enough samples for each person. The success of our approach is demonstrated by extensive experimental findings on the MORPH II, Cha Learn LAP 2015, and Cha Learn LAP 2016 datasets.

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#### IV. PROPOSED SYSTEM

The goal of image-based age estimate is to infer a person's age from their facial expressions. Numerous real-world applications make use of it. End-to-end deep models have show remarkable age estimation results on benchmark datasets, but due to the difficulties posed by wide changes in head attitude, facial expressions, and occlusions, their performance in the real world still has a lot of room for improvement. To solve this problem, we offer an easy-to-use but powerful technique for explicitly incorporating facial semantics into age estimation, allowing the model to develop the skill of correctly focusing on the most informative facial components from unaligned facial images regardless of head pose and non-rigid deformation. To represent facial semantic information at various levels, we incorporate both coarse and fine-grained features from a pretrained face parsing network and construct a tiny network on top of it to predict age. The proposed face parsing attention module and certain conventional operational layers are included in the proposed age estimate network. To predict age values, we start with a pre-trained model, remove the classifier, and then add our regression module. The regression module consists of several linear layers that combine to provide a single output that represents age values. The fundamental structure of the model is unchanged, but instead of having just one output at the conclusion of the regression module, we now have two outputs that indicate the separation between the images and our ranking value, which is derived from a sigmoid activation. The ROI with the highest score is chosen from the discovered ROIs, and the image is cropped with a respectable margin in the up, down, left, and right directions. This is done after recognising the ROI corresponding to the facial region by rotating the input image at various angles. This procedure corrects the rotational transformation in order to align the face image. By using the sorted image as an input to the Transfer Learning architecture, examining the value of the SoftMax layer, which is the architecture's output, as the likelihood of belonging to each class, and deriving the predicted value, this technique may estimate the age of the input image. Mean Absolute Error (MAE), a validation process typically used to measure the outcome of age estimation, is the average absolute value of the error of the estimate and the correct response.

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#### V. CONCLUSION

In this study, facial pictures of faces were used to estimate ages. to investigate facial recognition techniques in more detail. In comparison to the current machine learning method, the estimating method using transfer learning demonstrated substantial performance in the classification of gender and age. It was also more resistant to environmental changes. We have offered a straightforward but efficient method for estimating age by utilising face parsing semantics. We have created a framework to combine features from various face parsing network tiers. It is suggested to directly include facial semantics into the age estimation network using a novel face parsing attention module. In a different test set, the finished trained model was assessed, and it did reasonably well. To the best of our knowledge, this is the first attempt at age estimation using face parsing attention. We hope that the readers will be encouraged to think about using similar attention models for various deep face analysis problems after seeing our approach.

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#### VI. FUTURE ENHANCEMENT

Given that all models scored less favourably in the cross-dataset examination, an interesting direction for future work would be to look into domain shifts between various datasets and discover ways to minimise them.

It would also be interesting to expand the models to videos and investigate how to improve them with temporal information from movies, while the majority of works focus on image-based age prediction. These concepts will be investigated in the future.

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