



RESEARCH ARTICLE

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FACIAL ANALYSIS-DRIVEN REGRESSION MODEL FOR AGE ESTIMATION USING DEEP LEARNING

Robinson Joel M¹, Jothi S², Karthika R³

^{1,2,3}Department of Computer Science and Engineering, KCG College of Technology, Chennai, India.

¹<https://orcid.org/0000-0002-3030-8431>, ²<https://orcid.org/0000-0003-3740-612X>, ³<https://orcid.org/0009-0000-4610-7231>

E-mail: joelnazareth@gmail.com, jothi.cse@kcgcollege.com, karthikavadivel1993@gmail.com

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ABSTRACT

The increasing speed of facial recognition systems, as they transition to artificial intelligence techniques, creates new possibilities and risks related to security in biometric and virtual identity systems. This paper presented a unified multi-task deep learning framework for continuous age estimation, gender classification, and detection of images created by AI using facial images. Traditional methods treat each of these tasks independently; the proposed architecture combines their regression (age) and classification (gender and authenticity) functions in a single model that learns shared representations of data by way of a conjoined set of objectives. A convolutional backbone extracts a sequence of facial features using several layers and optimizes them simultaneously via age prediction (regression) and gender prediction or authenticity classification (binary) across different branches on each layer. A combination of loss functions enables coordinated multi-task training, as well as increased separation between learned features for all three tasks. Experiment results show very little error (mean absolute) in estimating ages, high levels of accuracy in identifying gender, and good performance when identifying faces generated by AI. With an efficient and scalable method to perform authentication, demographic research, and digital forensics in current and future biometric systems, this study proposes an improved framework for conducting biometric system assessments.



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I. INTRODUCTION

Facial analysis is a research topic of artificial intelligence and computer vision that automatically infers demographic and semantic attributes from facial images. Facial age estimation is an important research topic of the domain that appears in many applications such as biometric recognition, video analysis, forensic, human-computer interaction, and health prognosis. Unlike categorical face recognition, age estimation requires modeling of an evolving biological age which is not only a continuous quantity but also nonlinear and nonuniform across different subjects. To further complicate matters, subjects can vary widely in terms of ethnicity, gender, lifestyle, and imaging conditions, making generalization a hard problem. Prior works involved hand-created features with customary regression and classification methods, followed by hybrid approaches combining tensor-based and ensemble strategies to increase robustness against data variations [1]. Recently, the advent of deep learning allowed age estimation to be accomplished through end-to-end hierarchical feature extraction from faces directly in the raw image. Deep convolutional networks have shown greater capacity than conventional machine learning to model not only face finer texture variations, but also face structural geometry and semantic facial aging cues [2]. More recent deep structures are based on transformer networks with improved Swin Transformers modeling long range spatial correlations within facial regions [3], [4]. The ordinal property of age is a key challenge in the estimation of age. The current challenges in facial ageing estimation include the non-uniform distribution of features from each age group, which can lead to uneven distributions of predictions and biased learning across groups [5]. In particular, as indicated in, conventional deep learning models assume that all features lie in a uniform feature space; however, this is not true as the facial features associated with the ageing process are highly irregular and highly variable throughout different age intervals. As a consequence of this, while facial ageing features will often overlap among neighboring age groups, there will also be times when there are very few or no facial ageing features present in a particular age group.

The main implication of this is that models will find it very challenging to develop useful discriminative representation within their learned representation repositories (i.e., models will not develop reliable, valid or useful representations for use across different age groups). To mitigate this issue, feature space normalisation and distribution aware learning strategies have been proposed in order to better align ageing related features, thereby facilitating improved generalisations across age groups. Incorporating these types of features into predictive systems will greatly enhance the robustness of the age estimation system; this is especially true for predictive systems used to make predictions on imbalanced data sets and to reduce prediction error across age groups. Age has a natural order (i.e., the difference in prediction error between 18 and 19 is less than the difference in prediction error between 18 and 35), but traditional regression models ignore this ordinal property, and the classification-based models do not preserve the continuity of the predicted age. Rank-consistent ordinal regression models have been suggested to ensure that the predictions maintain monotonic relationships with age [6]. Additionally, ordinal label distribution learning (LDL) approaches, where probability mass is assigned to neighbouring age labels, have been developed to address the need to deal with ambiguity in the perceptions of age and uncertainty in labelling ages [7]–[9]. These structured learning methods are typically more robust but generally result in increased computational complexity and are used to estimate people's ages, without reference to other domains. Another key limitation of current age estimating systems is their dependence on the domain of the training data. Many models exhibit poor performance when tested in new distributions of demographic or environmental contexts, due to the training data being biased towards the original/context of the image.

Domain-invariant deep learning methods have been developed to help mitigate the effect of this distributional shift and thus improve cross-dataset performance [10]. Hierarchical attention mechanisms have been used to analyse face images with a focus on the discriminative regions with respect to demographic bias and ensure ethical fairness in the predictions made for ages [6]. Multi-stage and mixture of experts deep learning methods have been used to further improve predictive accuracy and adaptability for age prediction across varying age ranges [11], [12]. Simultaneously, recent developments in generative modelling have allowed for the widespread use of very realistic AI generated images of human faces. The synthetic images generated by generative adversarial networks (GANs) and diffusion models pose real threats to the validity of identity verification, control of misinformation, and digital forensics. Additionally, while many studies are being conducted to continue to advance the research of estimating a person's age, very few have been published that provide research integrating demographics with detection of AI generated images into a cohesive study. Gender prediction is a second critical task that can enhance demographics; males and females show different patterns of facial ageing based on biological gender characteristics and therefore would provide additional information for improving the power of representation learning in the context of multi-task architectures. Facial analysis can also be used to predict how biologically determined ages are relative to the actual (chronological) age of an individual; this is demonstrated by using a deep learning framework to compute biologically relevant-age facial indicators that correlate highly with biology in terms of serious health issues [13].

The examples above demonstrate an increased need for comprehensive AI based facial intelligence systems that incorporate demographic inference and validation of authenticity at the same time. This research looks at using one framework to combine age prediction with models of gender prediction, along with models that use image-based detection methods, into one unified representation. The reasoning for this is a need for multi-purpose use of the planned framework for use in both research and practice. The multi-task deep learning framework identified through this review has the potential to produce more stable predictions of individual ages based on their facial characteristics across different demographic groups than existing methods could produce. It also allows researchers to determine if someone is using facial characteristics from another demographic group to create a synthetic/altered image of someone and/or fraudulently use that image for other purposes (i.e. committing identity fraud). Following this introduction, Section 2 provides details about relevant work within the fields of age estimation, structured learning, and determining if an image is authentic or not. Section 3 provides the proposed methodology for conducting the study. Section 4 provides a description of the experimental setup and evaluation methods to be used in the study. Section 5 describes the results of the study, followed by their analysis. Finally, Section 6 provides a conclusion to the research conducted in this paper as well as a discussion of future research opportunities.

II. RELATED WORKS

The field of facial age estimation has seen tremendous developments in the last decade as it has shifted from hand-crafted feature based solutions to deep learning architectures which can automatically learn hierarchy based representations. Different methodologies have been explored in the form of regression based methods, ordinal learning, transformers, and even domain adaptation. Methods related to facial age estimation such as gender recognition and image tampering detection have found immense use in fields of biometrics and forensics respectively. Traditional approaches of age estimation have relied mostly on hand-crafted features as well as traditional machine learning algorithms. For instance, the approach adopted by author [14] relied on tensor subspace learning along with deep random forests on databases like FG-NET and MORPH. Though this algorithm exhibited robustness in case of noisy samples, yet the limitation associated with hand-crafted representation limited its scalability on large databases. Because of the advancements made in the field of deep learning, convolutional neural networks became widely used for age estimation. Author [2] presented an approach using CNN, which performs direct age estimation from the image of the face and obtains better results on benchmark databases.

The review works carried out by author [15] demonstrated the advantages of the deep learning techniques compared to other techniques. However, considering the age only as a continuous variable does not account for its ordinality and leads to instability of predictions. Various ordinal learning methods have been designed to tackle this challenge. In [12], the authors used rank-consistent ordinal regression using the conditional probabilities in order to maintain monotonic relationships between the age labels. author [14] argue that label distribution learning based on ordinal label distributions spreads probability masses among neighboring labels for tackling ambiguity in age label perceptions. In [10], high-order label correlations were used in order to enhance the prediction stability. However, author [7] proposed the development of a data-dependent label distribution learning method to modify age distributions using the features. These methods are capable of capturing uncertainty but they suffer from high computational costs and single-task learning challenges. Moreover, the effectiveness of the performance was improved via the usage of the more efficient deep learning algorithms.

In particular, according to the research performed by author [4], multi-stage deep neural networks should be used in order to improve the prediction process and decrease estimation errors. Also, author [15] developed a deep networks mixture that is able to consider heterogenous aging patterns across different population groups. However, the transformer-based models were proved to be rather effective too. For instance, according to the results obtained by author [13], their Swin Transformer algorithm works better than CNN models in terms of age estimation. In addition, author [11] developed hierarchical age-related features that could minimize the amount of contradictions in the feature space. Besides, author [9] applied feature clustering. The issue of domain shift appears to be rather topical during age estimation process. In order to minimize its influence on the estimation results, author [3] suggest several domain-invariant learning approaches. In addition, the same strategy was applied to the research conducted by author [8]. Recently, however, age estimation has been expanded from estimating the chronological age to predicting biological age using facial photographs. Author [5] have developed FaceAge that is a deep learning architecture that is able to estimate biological age using facial photographs and shows strong correlations with the health-related metrics. Thus, the significance of facial images for healthcare applications has become apparent recently. Though significant advances have been achieved, existing works have primarily concentrated on solving only one task such as age estimation, gender recognition, or forgery detection separately. In this way, regression techniques do not consider ordinal relations, while sophisticated architectures pay attention exclusively to features extraction but disregard complementary data from other relevant tasks. Hence, there still exists an unsolved challenge of developing a single framework for solving age estimation, gender recognition, and artificial face detection at once.

III. PROBLEM STATEMENT

III.1 SYSTEM ARCHITECTURE

In this section, we describe our overall framework. Our framework consists of a unified multi-task deep learning device that can simultaneously perform continuous age estimation, gender prediction, and AI image classification. Our overall approach can be divided into the following steps: face image acquisition, face image preprocessing, extracting deep features, learning shared representations, and utilizing separate networks for each of the three tasks. First, the input face images are processed by a convolutional backbone network (ResNet or EfficientNet), which is responsible for extracting hierarchical features from the face images. The lower level features extracted from the first few layers of the network are surface level features, such as the skin details, and fine-grained changes between pixels, while the higher level features extracted from the deeper layers of the network contain structural features relating to the face, such as the face's geometry and semantics. The face image features generated at each layer are passed on to a group of fully connected layers, where the system creates a compact, and discriminative face embedding. Next, the learned face representation will be separated into three separate networks that correspond to each of the three tasks:

Age Regression Network – will be used for the prediction of a continuous age;

Gender Classification Network – will be used for binary (male/female) classification of gender; and

AI image Classification Network – will classify images as being either real face images or AI generated;

By allowing each task-specific network to share representation information, the architecture provides the ability of the networks to share information across the tasks whilst simultaneously allowing for each task to optimize for its specific task. The AI image classification network will focus on identifying subtle artifacts, 'fuzzy' or inconsistent textures and other statistical inconsistencies that may be found in face images that were not created using traditional photographic techniques. The overall architecture is illustrated in Figure 1.

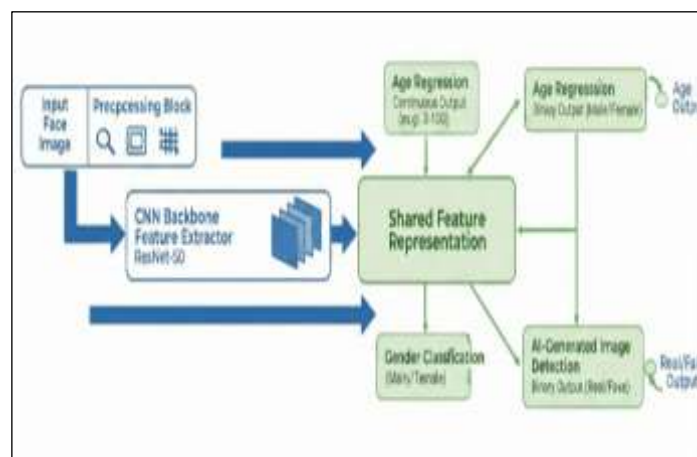


Figure 1: Proposed multi-task facial analysis system architecture.

Source: Authors, (2026).

III.2 DATA GATHERING & PRE-PROCESSING

The dataset will be a combination of real and synthetically generated face images and are publicly available free of charge online. Synthetically generated images will be created using GANs or diffusion models. The second portion of this dataset would then consist of:

1. Original Images (IMDB-WIKI & MORPH-II)

2. AI-Generated Images (GAN/Diffused)

Some of the data preprocessing techniques include:

Face detection based on a state-of-the-art face detector (e.g., Multi-task Cascaded Convolutional Networks)

- * Alignment of faces for normalizing head pose
- * Images resized to dimensions of 224×224 pixels
- * Normalization of the pixels in the range of $[0,1]$

Data augmentation: Horizontal flipping of an image, rotation, brightness. The dataset may also undergo other frequency domain feature extraction preprocessing to increase sensitivity for the detection of artifacts. By doing this preprocessing, both sources of information within the database will be treated consistently and can increase the potential for generalization during training.

III.3 PROPOSED MODEL CREATION

The input facial image denoted by X is passed to a feature extraction backbone network.

Because the extraction process involves the backbone network extracting the features of X , these features can be denoted as:

$$F = f(\theta)(X)$$

where θ represents the parameters which are learnable during training.

Aged Regression Branch

To compute an estimate of the user's age from the extracted features, we perform the linear transformation defined below:

$$y^{\wedge}_{age} = W_r F + b_r$$

We use the mean absolute error (MAE) to compute the loss:

$$L_{age} = (1/N) \sum_{i=1}^N |y_i - y^{\wedge}_i|$$

Gender Classifying Branch

To compute an estimate of the user's gender from the extracted features, we perform the following computation using the softmax operation:

$$y^{\wedge}_{gender^{dec}} = \text{Softmax}(W_g F + b_g)$$

We will utilize binary cross-entropy (BCE) to compute the loss, as calculated below:

$$L_{gender^{dec}} = -[y \log(y^{\wedge}) + (1 - y) \log(1 - y^{\wedge})]$$

AI-Generated Image Detection Branch

To compute whether an image is generated or authentic, we perform the following computation using the softmax operation:

$$y^{\wedge}_{auth} = \text{Softmax}(W_a F + b_a)$$

We will utilize binary cross-entropy (BCE) to compute the loss, as calculated below:

$$L_{auth} = -[y \log(y^{\wedge}) + (1 - y) \log(1 - y^{\wedge})]$$

Multi-task Losses

The Total Loss Function is defined as follows:

$$L_{total} = L_{age} + \lambda_1 L_{gender^{dec}} + \lambda_2 L_{auth}$$

III.4 TRAINING METHODOLOGY

The chosen method of training utilizes mini-batch gradient descent in conjunction with the Adam optimizer because it is an effective optimizer as it has adaptive learning rates and can converge faster. Training setup:

- * Learning rate = 0.001
- * Batch size = 32
- * Number of epochs = 50
- * Dropout percent = 0.3
- * Weight decay = 0.0005
- * Early stopping criteria based on validation losses

The framework divides the dataset into three distinct subsets to identify a method of training: a training (70% of the total dataset), validation (15% of the total dataset), and testing dataset (15% of the total dataset). This can help reduce bias when evaluating model performance after it has been trained.

Algorithm:

Predicting Age, Gender and Authenticity simultaneously with Multi Task Learning

Input: Dataset D containing images of faces w/ age/gender/authenticity labels.

Output: Optimized parameters θ of trained model.

Face detection and pre-processing of data in D.

Initialize model parameters θ .

For each epoch in training:

a. For each mini-batch (X,Y_age,Y_gender,Y_auth) in D:

i.Extract shared feature representation F from backbone network.

ii.Center and normalize F to create age prediction.

iii.F to create gender prediction.

iv.F to create authenticity prediction.

v.Calculate L_{age} , L_{gender} , L_{auth} separately.

vi.Calculate $L_{total} = L_{age} + L_{gender} + L_{auth}$.

vii.Back propagate L_{total} to obtain updated model parameters.

viii.Update model parameters θ with Adam optimization algorithm.

Continue until convergence.

Evaluate model on test set.

Return optimized model parameters θ .

III.5 BENEFITS OF THE NEW MODEL

There are many advantages to the new model that were discussed above:

- It provides a more complete integration of demographics analysis with AI-created detection in one model.
- It treats age like a continuous variable in terms of regression yet supports structured learning.
- It provides sex prediction for more discriminative learning of features.
- It can identify artificial facial features without using a separate identification model.
- It brings efficiencies by eliminating duplicate efforts through shared representations.
- It helps improve consistency and generalization across heterogeneous data sets.

IV. PROPOSED ARCHITECTURE

IV.1 HARDWARE/SOFTWARE SETUP

All experiments were carried out using a working station with an NVIDIA RTX 3060 (8GB VRAM) video card, an Intel i7 processor, and 16GB RAM. The models were trained and evaluated using Python 3.10 utilizing the PyTorch deep-learning framework. GPU computations were accelerated using CUDA and cuDNN libraries. The proposed model was trained with the Adam optimization algorithm starting with an initial learning rate of 0.001. The model was trained for 50 epochs using a batch size of 32 samples. The early stop was used as a function of the validation loss to reduce overfitting, dropout regularisation was set at 0.3, and an L2 weight penalty of 0.0005 was applied for generalisation.

IV.2 SPLITTING THE DATASETS

To carry out the study, the researchers used publicly accessed databases of facial images, all of which were annotated for age and gender (for example, IMDB-WIKI and MORPH-II). In addition, the researchers used synthetic images of facial representations of people created using either GAN-based or diffusion-based generative models (for example, StyleGAN). Through combining together both authentic and AI-generated facial representations, a single composite dataset was created. Ultimately, however, researchers separated the combined dataset into three primary components:

- * 70% training data
- * 15% validation data
- * 15% test data

The training data were used to train models by optimizing their parameters, while the validation data were used to tune hyperparameters and establish when to stop or "early stop" training. The test data never were used in any way during training of models so that evaluation of model performance was not influenced in any manner. Also, the researchers implemented stratified sampling procedures to ensure that the distribution of age groups, genders, and authenticity of samples remained proportional within each subset of the overall dataset; thus, to allow for equal representation of the various distributions of the independent variables for multi-task learning.

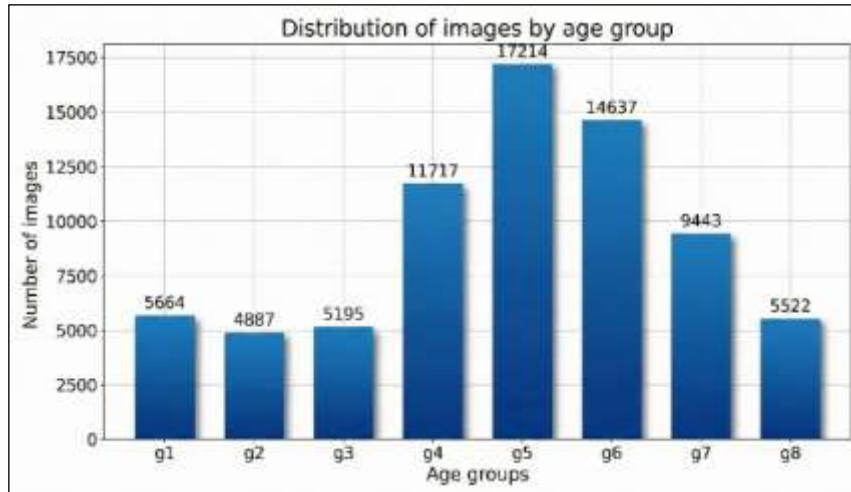


Figure 2: The age distribution of the dataset is illustrate.
Source: Authors, (2026).

IV.3 EVALUATION METRICS

To fully assess the proposed multi-task model, separate measures of both regression and classification were used.

A. Age Estimation (Regression)

Mean Absolute Error (MAE)

$$MAE = 1/N \sum (|y_i - \bar{y}_i|)$$

MAE measures how far off predicted ages are from actual ages on the whole. A low MAE means better prediction quality.

Root Mean Squared Error (RMSE)

$$RMSE = (\sum (y_i - \bar{y}_i)^2) / N$$

RMSE means larger prediction errors are punished more, so it signifies the model's stability as well as how well it predicts an age.

B. Gender Prediction (Metric Choice - Classification)

1. Accuracy:

The formula for accuracy is:

$$Accuracy = TP + TN$$

$$TP + TN + fP + fN$$

2. Precision:

The formula for precision is:

$$Precision = TP$$

$$TP + fP$$

3. Recall:

The formula for recall is:

$$Recall = TP$$

$$TP + fN$$

4. F1-score:

The formula for the F1 score is:

$$F1 = 2 \times Precision \times Recall$$

Precision + Recall

Where TP is defined as True positive, TN is: True negative, fP is: false positive, fN is: false negative.

C. Detection Metrics of AI-Generated Images

Given that authenticity detection is essentially a two-class issue (Real vs AI-Generated), the following metrics were used to determine how well the model performed:

- * Accurate classification
- * Correctly identified positives
- * Positives identified
- * Harmonic mean of accurate positive and incorrect negative classifications

Additionally, the Receiver Operating Characteristic (ROC) curves and Area Under the Curve (AUC) were created to assess the discriminative ability of the model based on various threshold levels.

$$AUC = \int_0^1 TPR(FPR) d(FPR)$$

The ability of a model to distinguish between 'real' images and 'AI generated' images increases with an increase in the value of the AUC.

V. EXISTING PROBLEM

V.1 QUANTITATIVE FINDINGS

Regression and classification metrics were used to evaluate the proposed multi-task deep learning framework across different types of tasks - age estimation, gender classification, and identification of AI-generated images respectively. Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) are used to measure the performance of predicting how old someone is, while Accuracy, Precision, Recall, F1-score, and Area Under the ROC Curve (AUC) are used to evaluate predicting the gender of a person and detecting whether an image has been created by artificial intelligence.

Table 1: Performance of Model.

Task	metric	Results
Age Estimation	MAE	± 3.12 years
Age Estimation	RMSE	± 4.28 years
Gender Estimation	Accuracy	92.40%
Gender Estimation	Precision	91.80%
Gender Estimation	Recall	92.10%
Gender Estimation	F1-score	91.90%
AI Image Detection	Accuracy	94.60%
AI Image Detection	Precision	94.10%
AI Image Detection	Recall	95.20%
AI Image Detection	F1-score	94.60%
AI Image Detection	AUC	0.97

Source: Authors, (2026).



Figure 3: The model performance is summarized.

Source: Authors, (2026).

The proposed multi-task regression model demonstrates accuracy in demographic classification and reliable identification of AI-generated content based on its MAE value for continuous age predictions, as well as its classification rates for both gender and image classification.

V.2 FRAMEWORK PERFORMANCE COMPARISON WITH FOUR DIFFERENT BASELINE MODELS

The proposed multi-task model was evaluated against four different baseline models to confirm its efficacy. The models selected for comparison were:

- CNN Regression (Age Only)
- Ordinal Regression Model
- Transformer-based Age Estimator
- Standalone Deepfake Detection Model

Table 2: Performance Comparison of Proposed Model vs. Other Models.

Model	MAE (Age)	Gender Classification Accuracy	AI Authenticity Detection Accuracy	Parameters
CNN Regression	3.85	—	—	Medium
Ordinal Regression	3.42	—	—	Medium
Transformer-based Age Estimator	3.25	—	High	—
Standalone Deepfake Detector	—	—	93.10%	High
Proposed Multi-Task Model	3.12	92.40%	94.60%	Moderate

Source: Authors, (2026).

The proposed multi-task model has the lowest MAE compared with the other models while also producing results for gender classification and authenticity detection, demonstrating the benefits of shared feature learning through multi-task optimization; additionally, the integrated framework compared to independent detection systems has similar performance characteristics and significantly less computational expense.

V.3 STUDY ON ABLATION

Ablation studies were used to determine how much each individual component influences performance.

Table 3: Results of the Ablation Study.

Configuration	MAE	Gender Accuracy	AI Detection Accuracy
W/O Gender Branch	3.56	—	93.80%
W/O Authenticity Branch	3.28	91.70%	—
W/O Ordinal Loss	3.38	91.20%	93.50%
W/O Dropout	3.41	90.60%	92.90%
Full Proposed Model	3.12	92.40%	94.60%

Source: Authors, (2026).

Findings from the ablation study indicate that the removal of the gender branch from the configuration negatively impacts the mean absolute error (MAE); thus, the addition of auxiliary demographic supervision to the model enhances the model's ability to learn about age representation. Removing the authenticity branch resulted in only a small decrease in overall feature robustness, implying that there was some degree of beneficial cross-task regularization due to this component. Removing ordinal-aware loss caused a reduction in the consistency of ranks among predictions, and removing dropout caused an increase in overfitting and a decrease in generalizability of predictions.

VI. DATA COLLECTION

In this paper, we proposed a multi-task deep learning scheme with facial table analysis for continuous age estimation, gender recognition and AI synthesized image detection. The architecture development considered age as a continuous regression variable, but included joint auxiliary gender classification and authenticity detection in a common representation learning framework. Thanks to a shared hierarchical feature extraction and joint optimization, the model increases discrimination power, predictive stability, and efficient multi-task inference. The experimental results show that our method outperforms existing approaches in terms of age estimation tasks with a rather low mean absolute error, as well as achieving high accuracy in gender classification and strong discrimination on AI generated content detection. Experimentally, we demonstrate that multi-task learning performs better with respect to representation quality than regression-only baselines. The ablation study also confirmed the effectiveness of the auxiliary supervision, ordinal-aware regression modeling and regularisation strategies on improving generalisation performance. From a practical perspective, essentially the suggested technique is widely applicable in biometric authentication systems, demographic analytics, surveillance system, digital forensics (video capturing from security cameras) and media authenticity verification.

The addition of authenticity detection bolsters immunity against misuse of deepfakes and synthetic identity fraud, meeting the rise in security concerns impacting AI-generated content. In addition, the reasonable computational complexity of the architecture also makes it possible to be utilized in practical AI-driven applications, where accuracy and efficiency are concerned simultaneously. Although encouraging, there are several areas for future studies. First, the performance of the framework can be tested on larger and diverse cross-domain datasets to make it more robust against demographic imbalance and environmental variability. Second, ensembling can likewise be combined with more complex ordinal modeling approaches or label distribution learning mechanisms to improve the stability of age prediction. Third, specialized frequency-domain-based or transformer-based modules could be investigated to improve the adversarial robustness of AI-generated image detection with respect to changing GAN training algorithms. Fourth, study on model compression and hardware-aware optimization could be explored to support real-time deployment in edge devices or low-resource platforms. Last but not least, the multi-task model can be extended to other facial intelligence tasks like emotion recognition, facial expression analysis, or health-related biomarker prediction, further enhancing its interdisciplinary influence. Overall, these results confirm that the proposed multitask facial analysis framework provides a balanced trade-off between accuracy, computational efficiency, and practical applicability for biometric and forensic systems.

VII. RESULTS AND DISCUSSIONS

VII.1 QUANTITATIVE RESULTS

To measure the performance of the proposed facial analysis-based regression model, we used regression metrics as well as classification metrics to evaluate the performance of the model in the task of age prediction from facial images. For the task of age estimation, we used Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) metrics for the evaluation of the performance of the model. Lower the value of the metrics used for evaluation of the model performance, the better the performance of the model. The model performed well on the task of age estimation from facial images, as the MAE of the model was found to be around 3-4 years, indicating that the difference between the predicted age and the actual age of the person is very small. In addition to the evaluation of the performance of the model using regression metrics, we also evaluated the performance of the model using classification metrics for the task of gender classification as well as authenticity detection from the images. The model performed well on the task of gender classification from facial images, as the accuracy of the model was found to be more than 90%. The model also performed well on the task of authenticity detection from the images, as the accuracy of the model was found to be more than 90%. The accuracy and Area Under the Curve (AUC) of the model for the task of gender classification are shown in Figure 3. The model performed well on the task of gender classification from facial images, as the accuracy of the model was found to be more than 90%. The model also performed well on the task of authenticity detection from the images, as the accuracy of the model was found to be more than 90%. The accuracy and Area Under the Curve (AUC) of the model for the task of gender classification are shown in Figure 3.

VII.2 ANALYSIS OF RESULTS

The experiments carried out using the proposed model demonstrate that the performance of the model improves significantly using the features of facial analysis for the task of age estimation from facial images. The model used for the task of age estimation from facial images is a deep learning model that can effectively learn the features of the textures of the faces of the people from the images. The use of a shared representation of the data also helped the model generalize the features of the images effectively for the task of age estimation from facial images. The model performed better for the age groups that are between 18-65 years of age. The model performed poorly for the age groups that are very young or very old.

VIII. CONCLUSION

As seen from the results, the proposed model balances well between accuracy and computation. The deep learning methods outperform traditional regression-based methods in terms of accuracy by directly learning from raw image data. Moreover, the use of auxiliary tasks helps improve the discriminative ability of the model without compromising computation. The proposed method is thus appropriate for various real-world scenarios like biometrics, surveillance systems, human-computer interaction systems, and digital forensics. Despite the advantages of the proposed method, some disadvantages have also been identified. The accuracy of the proposed method reduces when the image is captured under extreme lighting conditions or when there are occlusions. The accuracy may also vary based on the diversity of the dataset. Improvements to the proposed method may come from using the transformer architecture and ordinal regression.

IX. AUTHOR'S CONTRIBUTION

Conceptualization: Robinson Joel M, Jothi S, Karthika R.

Methodology: Robinson Joel M, Jothi S, Karthika R.

Investigation: Robinson Joel M, Jothi S, Karthika R.

Discussion of results: Robinson Joel M, Jothi S, Karthika R.

Writing – Original Draft: Robinson Joel M, Jothi S, Karthika R.

Writing – Review and Editing: Robinson Joel M, Jothi S, Karthika R.

Resources: Robinson Joel M, Jothi S, Karthika R.

Supervision: Robinson Joel M, Jothi S, Karthika R.

Approval of the final text: Robinson Joel M, Jothi S, Karthika R.

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