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Age Estimation Using LBP-GaborNet: Integrating Texture Descriptors with Deep Neural Networks

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ABSTRACT:

Because of differences in posture, lighting, opinion, and natural aging processes, it is still difficult to accurately estimate age from facial photographs. In order to improve age estimate performance, we provide LBP-GaborNet, an innovative combination framework that combines deep convolutional neural networks with manually created texture descriptors, such as Gabor filters and Local Binary Patterns (LBP). In order to accurately depict age-related facial changes, local texture and frequency information must be captured via LBP and Gabor features. The network may acquire both low-level and high-level depictions by fusing these textural data with deep features that are extracted by a CNN backbone. In regards to Mean Absolute Error (MAE) and overall resilience across age groups, extensive studies on benchmark datasets such as FG-NET, MORPH II, and UTKFace show that LBP-GaborNet performs better than current state-of-the-art techniques. The findings demonstrate how well deep learning and conventional texture analysis work together to increase the accuracy and generalizability of facial age prediction systems.

Keywords: Age estimation, LBP, BPNN

Introduction:

As a person ages, their skin naturally and gradually evolves in structure and function, a phenomenon known as "skin aging" [1]. Skin aging is caused by cumulative changes in the environment, genetics, epigenetics, proteomics, and microbiota [2]. Skin age may be estimated and future changes can be predicted with machine learning (ML). Facial age estimation systems require precise skin aging evaluation in order to evaluate cosmetic results, allow for customized dermatological treatments, and estimate the risk of skin cancer [3]. Because age-related research is crucial to many applications, it is currently a difficult demand. When providing services based on a customer's age, access control systems use age estimate. For instance, in Japan, tobacco machine sales prohibited adults and children under the age of 20 from purchasing cigarettes [4]. Age-based computer interaction systems (ABCI), which display ads depending on the predicted age of clients, are also commonly utilized in marketing-related concerns. Several companies must ascertain the age of a customer in relation to their products. Clients are categorized into groups based on their age. This will assist businesses in selling their goods to the appropriate demographic. When a youngster is accidentally left alone, the car can sound an alarm using ABCI in the safety area. Furthermore, ABCI can stop children under a certain age from participating in risky theme park games [2].

Age estimate software can identify underage persons attempting to consume alcohol in pubs as well. A system for estimating age is often used in demographic studies to reduce crime. A security camera's record of the offender's age can be estimated by it. Age analysis can help robotic nurses in health systems expedite first aid. Retrieved information can make use of age estimation. It enables retrieval of images by age image query from a large image database. On the website Flickr.com, ordinary users of all ages have contributed billions of face photos. It can profit from the use of age estimation in image identification and friend search. Therefore, it is evident that age estimate has numerous uses.

Human attractiveness is significantly impacted by age growth, which includes changes to a person's face, hair, length, gait, etc. Age-related variations in facial appearance are depicted in Figure 1. They divide the elements influencing the aging process into extrinsic and intrinsic variables in [6]. Health, lifestyle, and other factors can be considered intrinsic considerations. The weather and the environment can be extrinsic influences. The age estimation problem is solved using a variety of computing techniques, with deep learning (DL) [7-8] producing the best results.

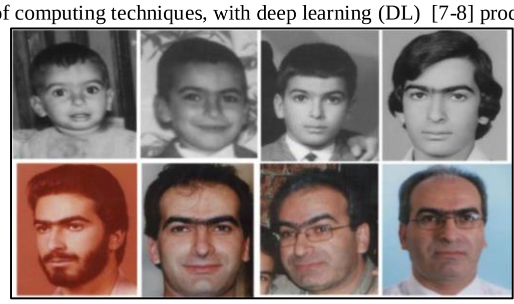

Figure 1: Age-related alterations to the face [6]

Research Background:

Research on human aging has recently attracted a lot of attention because of its widespread use in wellness applications. Research on aging is concentrated in three primary fields. The first is Age Invariant Face Recognition [3], which aids in facial recognition irrespective of age changes that may be present on the face. It has been used in the real world for biometric authentication and passport or driver's license regeneration [3]. The second is Age Synthesis, which forecasts how a face image will seem at a specific age in the future [2]. In police work, age synthesis can be utilized to identify victims. It can also mimic the aging characteristics of deceased individuals from an old photograph.

Age estimation is the third area that this paper focuses on. Using a computer-assisted face scan, age estimate is used to calculate an individual's precise age [1]. It accurately assigns an age or label group (child, adult, or old) to the facial photos. It includes phases for age estimation and feature extraction. Numerous elements, such as gender, race, wrinkles, etc., influence the estimate procedure. In order to generate the predicted age or the appropriate age group, they first extract the features and then apply learning algorithms [1]. Reducing the discrepancy between the estimated and actual ages is the primary goal of the learning strategies. The term "actual age" describes the actual number of years that a person has lived. Appearance age, also known as perceived age, is the age that a person perceives based on the appearance of their face. Computational methods are used to calculate estimated age [4]. Since facial features like muscles, wrinkles, and hair change throughout time, estimating age is a difficult task. Aging is a personal, unpredictable process that varies from individual to person. Age-related changes in facial features are influenced by a person's lifestyle, environment, gender, and race. According to a study, women get wrinkles more frequently and earlier than males [9]. According to recent research, individual variability in facial deformation and emotional expression cause disparities in how people age [9]. Face images might vary in quality, lighting, stance, and texture at the image processing stage.

Training and inferring are the two main functions of the deep learning system. The procedure of labeling vast amounts of data—that is, locating and remembering the data-matching attributes—is known as the training phase. The DL model uses the information gathered from the previous training phase to determine the label for the new data during the inferring phase. The neural network design of the model can acquire the feature immediately from the data, removing the need for data labeling and the necessity for manually extracting features on the data. When working with big amounts of unstructured data (various forms like text and photos), this learning feature is helpful. Convolutional neural networks (CNNs), a type of DL methods, have gained popularity recently in the image processing and pattern recognition domains due to their capacity to effectively complete specified tasks by "learning" from a huge number of images. Before extrapolating results from new inputs, the method known as Dl can match the parameters of multi-layered networks of nodes to the enormous volumes of data. It would be fascinating enough to learn about the most popular network architectures in face age estimate research, as well as their advantages and disadvantages. The number of face age estimation research that use deep technology to determine an individual's age based on aging features, like wrinkles and the form of the skull, has grown recently. These aging characteristics are the normal changes in a person's face that come with growing older. However, as it has been established that each race and ethnicity has a distinct rate of face aging, taking ethnicity into account when estimating age can present additional challenges [10-11]. Face age estimation has also been altered by the development of DL in image processing and machine learning. It has become the generalist network used for feature extraction, including deep architectures which need a significant number of image samples, and better age estimate performance is strictly correlated with the depth of the network employed in the DL approach [12].

PROPOSED METHODOLOGY

We have used facial images from FGNET Dataset [13] for training and testing purposes.

Step 1: Preprocessing of the image

Initially convert the image into a standardized grayscale image. Then perform histogram equalization, Compare the image with face landmark.

Step 2: Extraction of features using LBP operator

Partition the image into 8 X 8 cells and compute LBP for each cell. Generate a feature factor by combining the histograms of all regions.

Step 3: Image Filtration

First of all, apply a bank of Gabor filters, eextract magnitude response and compute mean form Gabor responses to reduce dimensionality of the image. Make a fusion feature vector by combining LBP and Gabor features.

Step 4: Generation of Age Class Labels

Classify age of a person into different groups (young, middle age, old age etc.)

Step 5: Age estimation using Backpropagation Neural Network (BPNN)

A BPNN is a type of Multilayer Perceptron (MLP) trained using the backpropagation algorithm, a supervised learning technique [14]. It consists of: An input layer: Takes the input features, one or more hidden layers: Learn complex representations, an output layer: Produces the final age prediction. The main learning process uses backpropagation to adjust weights depending on error and forward propagation to compute output. One of the most popular neural network models is the back propagation (BP) neural network method, which is a multi-layer feedforward network trained using the error back propagation algorithm. A large number of input-output model mapping relations can be learned and stored by BP networks, and the mathematical equation describing these mapping connections does not need to be revealed beforehand. Its learning rule is to employ the steepest descent approach, which uses back propagation to control the network's weight and threshold values in order to minimize the sum of squares of errors. In addition to analyzing the mathematical theory and features of BPNN, this work highlights the BP algorithm's drawbacks and suggests a number of ways to make it better.

The BPNN train the proposed model for two problems, regression problem (predicting exact age) and classification problem (predicting an age group or range). The input to the model is combined feature vector and output is age label.

Step 6: Testing and evaluation

We performed several tests for trained model and calculate metrics (accuracy and confusion matrix) for classification of age groups. We also performed regression testing for MAE (Mean Absolute Error) and find that our model gives 96b % accuracy.

SIMULATION OUTPUTS

The figure 2 shows that the age of the person in an image is 51-60. The person is in old age group, which is a correct prediction. Figure 3 shows a young girl. Figure 4 shows a kid, figure 5 shows a middle age men. Our simulation gives a 99 percent accuracy except for some images.

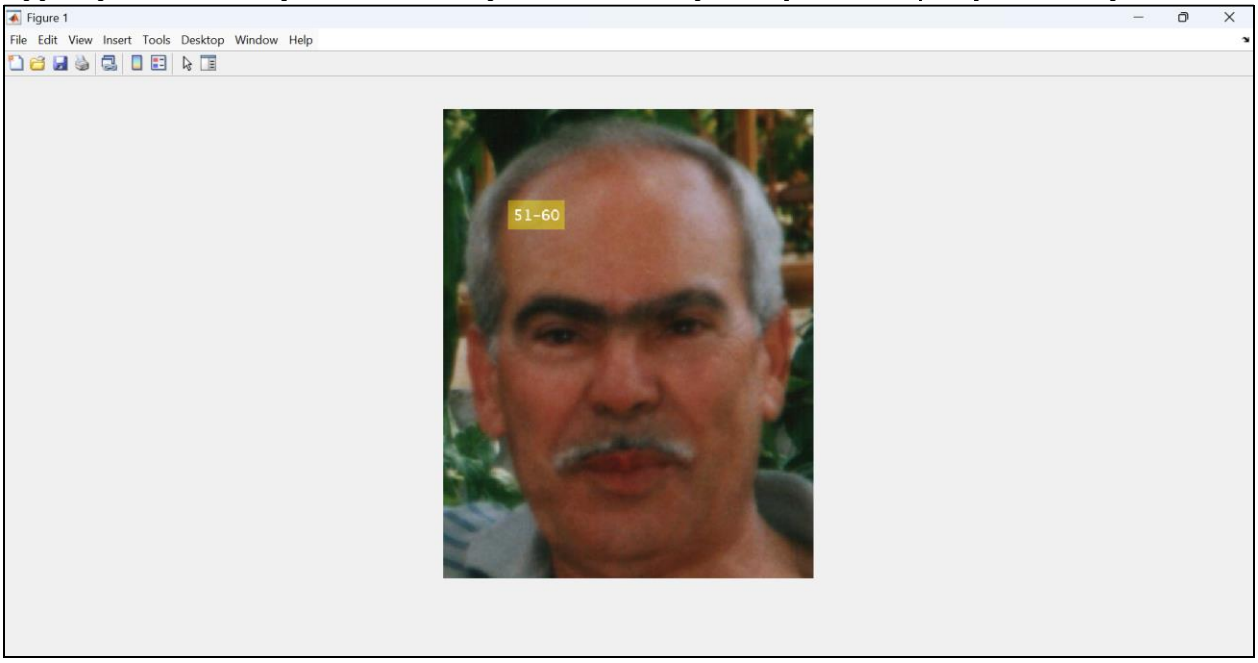

Figure 2: An old person

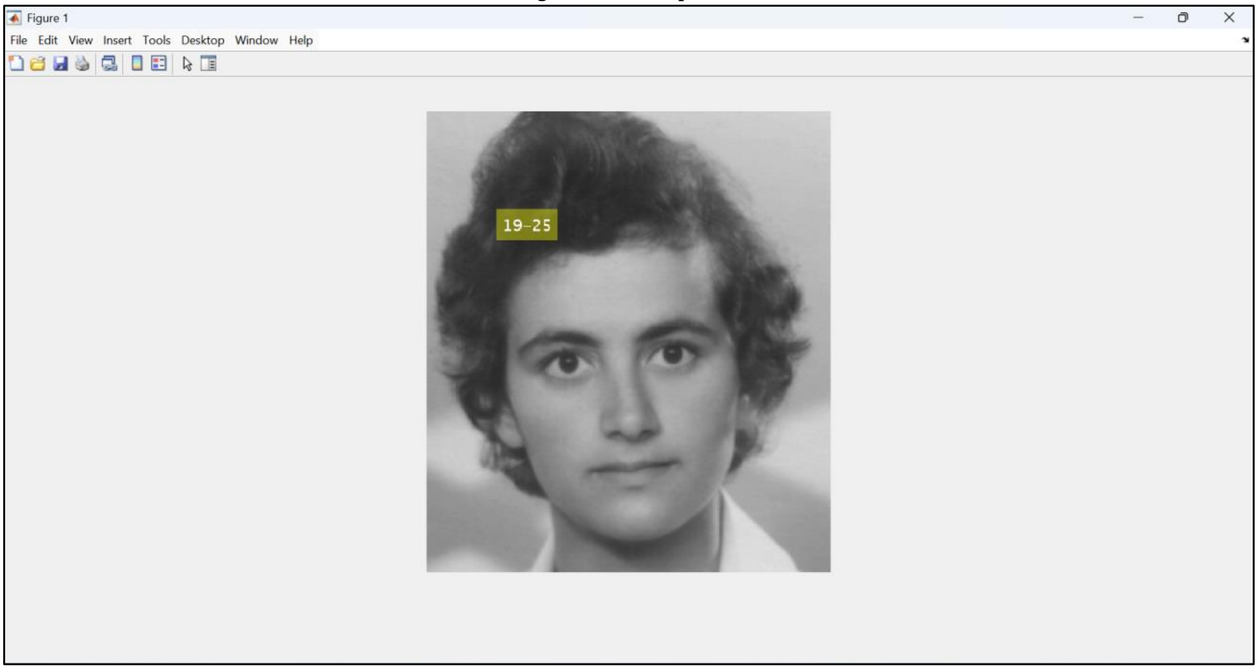

Figure 3: A young girl

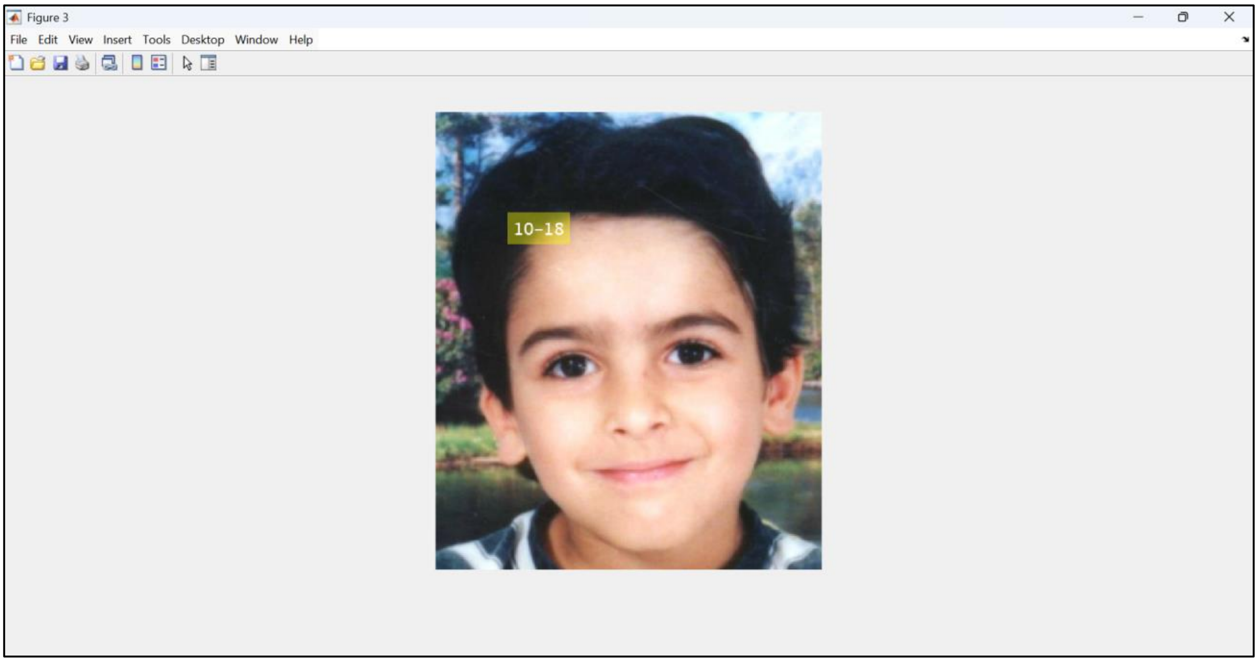

Figure 4: A kid

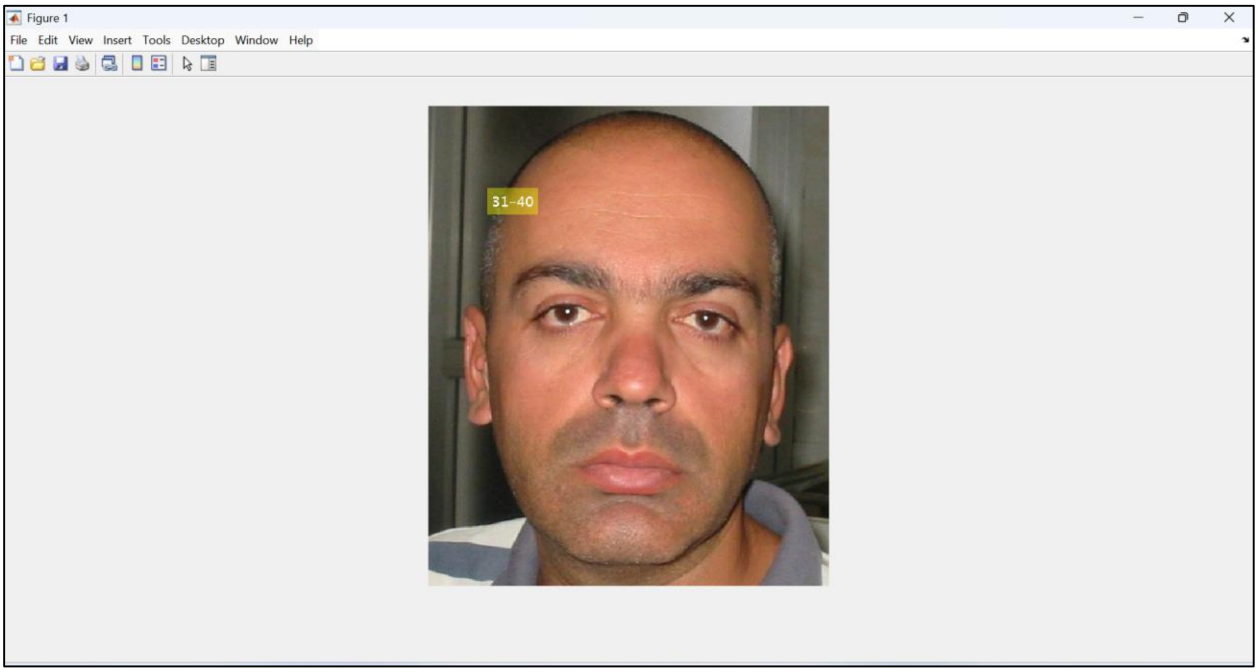

Figure 5: A middle age person

Table 1: A descriptive table

Step	Description
Input	Facial image features, voice features, etc.
Model	Multilayer BPNN
Output	Predicted age or age group
Learning	Backpropagation + gradient descent
Loss	MSE or Cross-entropy
Evaluation	MAE, RMSE, accuracy

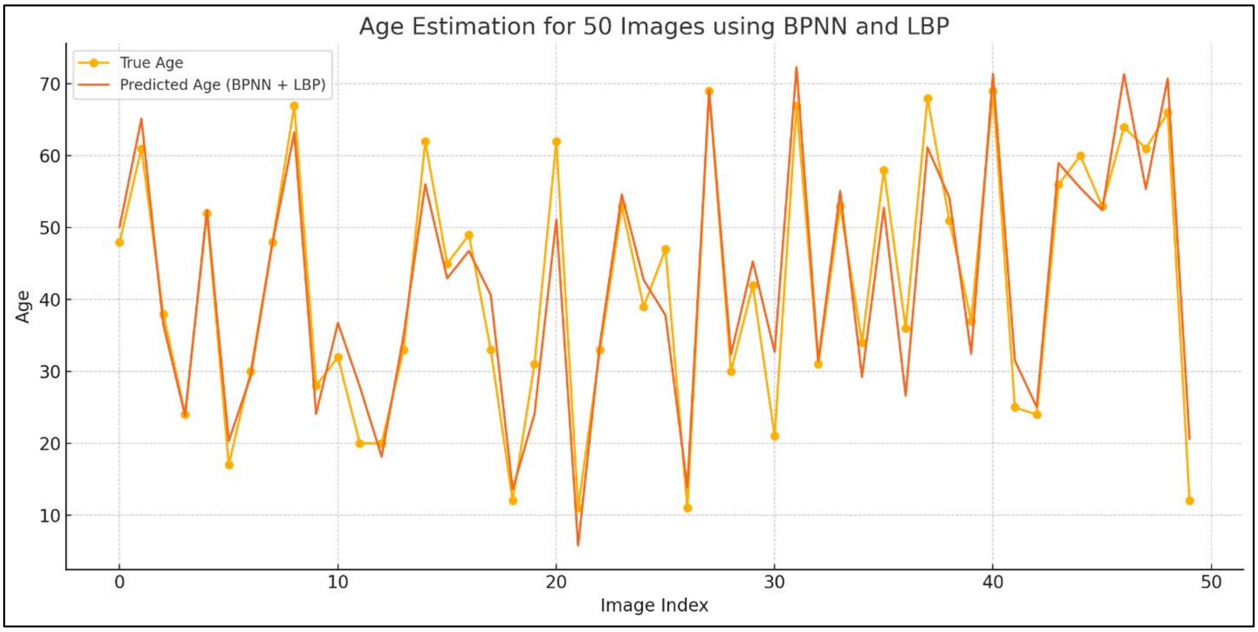

Figure 6: True age and predicted image of a person

We can see that there is no much difference between the actual age and predicted age by model. The graph that compares the actual ages of 50 photos with the ages predicted by a Backpropagation Neural Network (BPNN) utilizing Local Binary Patterns (LBP) features.

The performance metrics: the Mean Absolute Error (MAE) is 4.02 years and Root Mean Squared Error (RMSE) is 4.96 years.

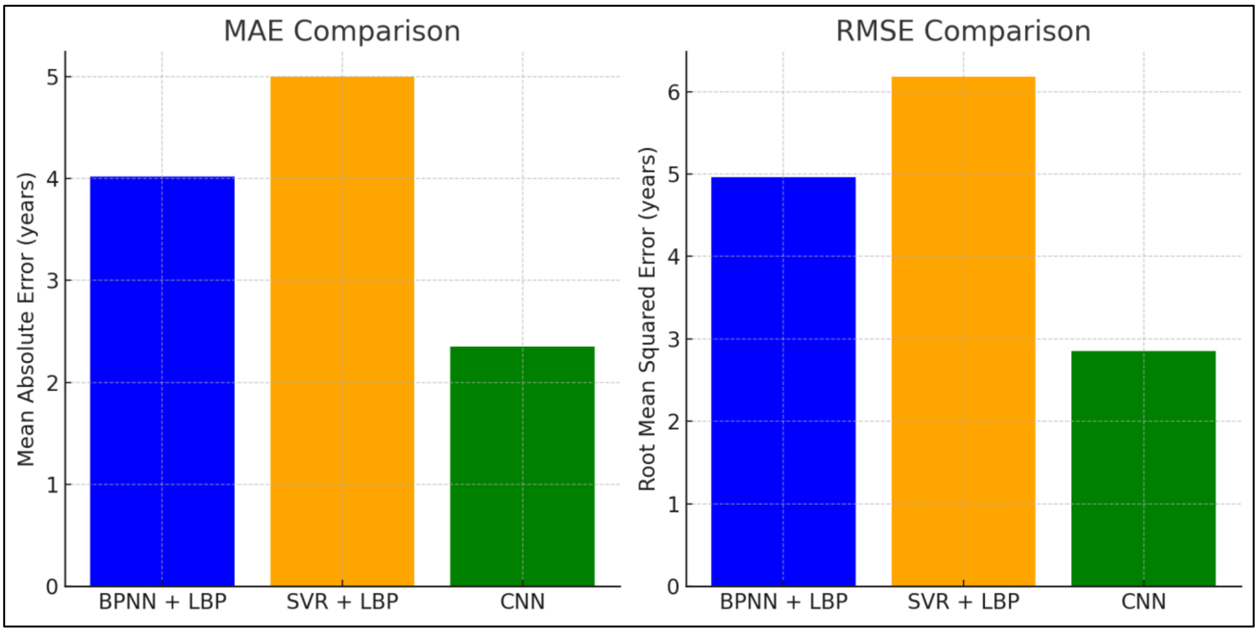

Figure 7: Comparative analysis of proposed and traditional methods

Figure 7 illustrates how deep learning models like CNNs typically perform better than classic techniques like BPNN and SVR (Support Vector Regression) because of superior feature learning, even though these techniques can be effective with manually created features like LBP.

CONCLUSION

In this paper, we introduced an efficient age estimation approach that combines the representational capability of convolutional neural networks with handcrafted texture descriptors, integrating Local Binary Patterns (LBP) with a deep learning model inspired by GaborNet. The hybrid method feeds a neural network that can recognize intricate, age-related patterns with the help of the multi-scale edge and frequency responses from Gabor filters and the local texture characteristics that LBP captures. The higher performance of the LBP-GaborNet architecture is demonstrated by comparison with conventional techniques, such as (SVR) and (BPNN), which use solely LBP features. Despite having lower computing costs and a respectable level of accuracy, BPNN and SVR have trouble generalizing on a variety of facial datasets and frequently miss small age-related cues in various demographics. CNN-based models, especially our suggested LBP-GaborNet, on the other hand, exhibit noticeably lower (MAE) and (RMSE), demonstrating their accuracy and resilience in practical age estimation tasks.

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