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Comparison of KNN and CNN Algorithms for Gender Classification Based on Eye Images

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Abstract.
Purpose: This study explores gender classification using iris images and compares two methods k-nearest neighbors (KNN) and convolutional neural networks (CNN). Most research has focused on facial recognition. However, iris classification is more unique and accurate. This research addresses a gap in gender classification using iris images. It also tests the effectiveness of CNN and KNN for this task.
Methods: This study used 11,525 iris images from Kaggle. Of these, 6,323 were male and 5,202 were female. The authors split the data into training (75%) and testing (25%). Preprocessing involved normalizing and augmenting images by rotating, scaling, shifting, and reflecting the them. Pixel values were also adjusted. The study compared the KNN algorithm, using Euclidean distance and 16 neighbors, with a CNN model. The CNN had layers for convolution, pooling, and density. The authors performed evaluation using accuracy, precision, recall, F1-score, and confusion matrix.
Result: The KNN model demonstrated 81% accuracy. It identified males with 87% precision but only 70% recall. Meanwhile, the CNN model was better, achieving 93% accuracy with 94% precision and 95% recall for males. The CNN model outperformed KNN for females in precision, recall, and F1-score, indicating its superior ability to learn patterns and classify gender from iris images.
Novelty: CNN outperforms KNN in classifying gender from iris images. It effectively recognizes patterns and achieves high accuracy. The study shows CNN's superiority in biometric tasks, suggesting that future research should balance datasets and test better models, as well as combining models for better performance.

Keywords: Biometrics, Classification, Convolutional neural networks, Eye image, Gender classification, KNN
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INTRODUCTION

The development of biometric technology is very important in many areas of life today, especially in identity authentication. Biometric identifiers in the form of fingerprints, face shapes, and iris features offer reliable uniqueness for individual identity recognition [1]. Iris recognition is particularly challenging due to its complexity and level of uniqueness, and therefore research in this field is constantly evolving. As artificial intelligence (AI) advances, biometric-based automation methods are becoming more reliable. AI, especially deep learning, is a potential method to improve the accuracy of biometric recognition [2], [3]. Biometric technology enables automatic recognition based on different characteristics [4]. In terms of image classification, convolutional neural networks (CNN) have taken the center stage due to their superiority in complex visual pattern recognition, including in face and gender recognition tasks [5].

Previous research conducted by [6], [7], [8], [9] has discussed the application of deep learning models using transfer learning, especially in gender classification. Research [10], [11], [12] have employed CNN models trained to recognize gender from facial images, while research by [13], [14] using CNN as a gender classification method based on fingerprints. K-nearest neighbors (KNN) is a supervised learning algorithm used for classification and regression. KNN predicts outcomes based on the nearest neighbor data points. It measures the distance between the new data and training data, then selects the k nearest neighbors to predict the majority class for classification, or the average for regression. KNN is simple but less efficient on large datasets due to the significant computational effort required for distance calculations [15]. Meanwhile [10], [16], [17] compared the performance of the KNN algorithm with Naive Bayes in gender classification. Images were converted to grayscale to extract texture features, and then classified using

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support vector machine (SVM), Naive Bayes, and KNN algorithms. The evaluation results showed that KNN achieved the highest accuracy of 90%, exceeding SVM [18]. Meaningful information from iris images was extracted and normalization was implemented to reduce illumination differences, and LDA was applied for dimensionality reduction and KNN and SVM as classifiers [19]. CNN has successfully overcome the challenge of extracting important details from images, especially in face recognition, where each convolutional layer of the network can identify relevant patterns automatically. However, challenges in recognition and classification based on specific features, such as the iris, remain a significant area for further exploration [20], [21].

CNN is proven to excel in object recognition and image classification thanks to its ability to cluster pixels simultaneously, which differentiates it from traditional algorithms that view images sequentially. This allows CNN to better understand temporal patterns [22], [23]. However, much of the existing research focuses primarily on facial image-based classification [24], [25], [26], [27], while only little attention is paid to iris-based classification, which has higher biometric uniqueness. This highlights a significant gap in the current research, as iris-based recognition offers more accurate results for gender classification. Therefore, more research is needed to overcome the challenges and improve the technique of gender classification using iris images [28], [29]. CNN has several layers, namely convolution, pooling, fully connected, and loss. The convolution layer is key, using filters to learn features and create a map, while the pooling layer simplifies this output, reducing complexity and boosting stability using max, min, or average pooling. CNN has two parts, namely feature extraction consisting of convolution and pooling as well as classification consisting of fully connected layer. Additionally, it also involves factors such as activation function, normalization, loss function, regularization, and optimization affect performance [30].

Previous studies have predominantly focused on gender classification using facial images. However, few studies have specifically examined gender classification based on eye images. In fact, the iris offers unique biometric features and has the potential to be more accurate in classification tasks. This study aimed to compare the performance of CNN and KNN for gender classification using iris images. It evaluated CNN performance and compared it to KNN, utilizing key metrics like accuracy, precision, recall, and F1 score to measure the robustness of the models. This research addresses a crucial gap in the existing literature, aiming to advance biometric classification methods, particularly for iris-based gender classification.

METHODS
This study utilized dataset collection and research methods with explanation as follows.

Dataset
The datasets used in this research to classify gender based on eye images using KNN and CNN methods are presented in Figure 1.

Figure 1. Dataset

The dataset for this study was sourced from Kaggle [31]. It features 11,525 eye images: 6,323 male and 5,202 female. This study divided the dataset into two parts: a training set and a testing set.

Research method

The flow chart in

Figure *2* shows the research method utilized in this study, which involves data pre-processing and gender classification using KNN and CNN.

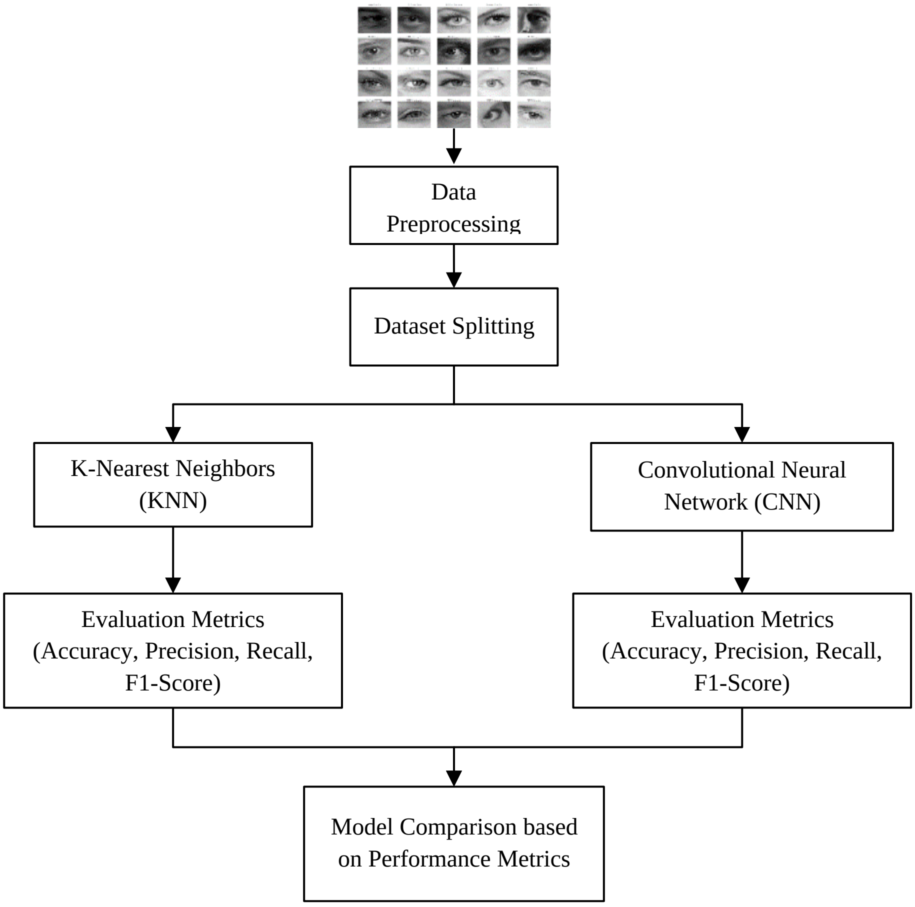

Figure 2. Research method

Data preprocessing

Data preprocessing is critical as it ensures consistent input quality for the model. This stage consisted of several main processes, including image data normalization and linear interpolation to standardize image sizes. The process was utilized to maintain the aspect ratio and quality and uses the following formula:

$$x_{new} = x_{old}\left(\frac{width_{new}}{width_{old}}\right) \tag{1}$$

$$y_{new} = y_{old}\left(\frac{width_{new}}{width_{old}}\right) \tag{2}$$

where:

x_{new}, y_{new}: pixel coordinates in the resulting image
x_{old}, y_{old}: pixel coordinates in the original image
$width_{new}, height_{new}$: target dimensions
$width_{old}, height_{old}$: original dimensions

The study augmented the data to add variety and prevent overfitting through the following processes:
Affine Transformation:

1. Rotation: Images were rotated by 20 degrees to train the model to recognize objects at different angles.
2. Horizontal and Vertical Shift: Images were shifted by 10% of its width and height to provide variation in the position of the object.
3. Horizontal and Vertical Reflection: Images were mirrored to showcase symmetry, which is vital for datasets with symmetrical objects.

Geometric Transformation:

1. Shearing Distortion (Shearing Transformation): Images were tilted by 0.2 on the x-axis to create a tilt effect.
2. Object sizes in an image were scaled, zoomed, or adjusted by 10% to add diverse sizes to the dataset and aid the model in recognizing objects at different scales.

Data normalization: This study normalized pixel values to homogenize the range of input values using the following formula.

$$x_{normlized} = \frac{x}{255.0} \tag{3}$$

The process converted pixel values from the range 0-255 to 0-1, helping the model in the learning process.

Dataset splitting

The dataset contained a training set (75%) and a test set (25%) to ensure that the model had sufficient data to learn the patterns. In the training dataset, there were a total of 11,525 images, with 6,323 labelled as male and 5,202 labelled as female. This helped the model learn the gender-based features of the eye images. In the test dataset, there were 2,882 images, with 1,594 labelled as male and 1,288 labelled as female. The test dataset allowed the authors to observe the model performance after training.

K-Nearest Neighbors (KNN)

KNN is a nonparametric algorithm and it classifies data by comparing it to its nearest neighbors.
Model Parameters:

Table 1. KNN parameters

Parameter	Value	Description
k (Neighbors)	16	The number of nearest neighbors to determine the new data class.
Metric	Euclidean distance	The distance used to determine the closeness of points: the Euclidean distance.
Weights	Uniform	All neighbors had equal weight in class determination. There was no particular neighbor preference.

The classification process calculated the Euclidean distance between the test data and all training data using the following formula:

$$d(X,Y) = \sqrt{\sum_{i=1}^{n} (xi - yi)^2} \tag{4}$$

where:
$X =$ test data feature vector
Y = training data feature vector
N = number of feature dimensions

Once the model identified the KNN, it applied a majority voting rule to determine the class. If k =16 and two of the three nearest neighbors belonged to male class, the prediction for that test sample would be male.

Convolutional Neural Network (CNN)

To create a CNN model, the hyperparameters were determined first. These included the activation function, loss function, epochs, and optimizer. The hyperparameters in this research are as follows:

Table 2. CNN Model Parameters

Type	Value
Batch size	32
Epoch	50
Optimizer	Adam
Learning rate	0.001
β_1	0.9
β_2	0.999
Loss function	Binary cross-entropy

The batch size of 32 indicates the data processed in one go. A bigger size means more stability but slower speed. The epoch value of 50 represents how often the model sees the full dataset. More epochs improve learning but with overfitting risk. The optimizer Adam blends momentum and RMSprop for efficient updates, while the learning rate of 0.001 speeds up the update process. Smaller values prevent big jumps but slow training. The values of β_1: 0.9 and β_2: 0.999 set the decay for gradients in Adam, while the loss function of binary cross-entropy measures the gap between true and predicted labels in binary tasks.
Convolutional Layer: The convolution operation applied filters (kernels) to the input image to produce feature maps. For an input image I and a filter F of size $k\ x\ k$,the convolution operation $S(i,j)$ was calculated as follows:

$$S(i,j) = \sum_{m=1}^{k} \sum_{n=1}^{k} I(i+m, j+n).F(m,N) \tag{5}$$

where:
I = input matrix
F= filter kernel
S= feature map result
i,j= position at the output
m,n= position on the kernel

Evaluation metrics

Accuracy: Accuracy is the ratio of correctly classified samples to the total. It shows how well the model works, but it can be misleading with imbalanced classes.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{6}$$

Precision: Precision measures how many of the samples predicted as positive are actually positive. It is especially useful when the cost of false positives is high.

$$Presicion = \frac{True\ Positives}{True\ Positives + False\ Positives} \tag{7}$$

Recall (Sensitivity or True Positive Rate): Recall measures how many actual positive samples the model predicted correctly. It is useful when the cost of false negatives is high.

$$Recal = \frac{True\ Positives}{True\ Positives + False\ Positives} \tag{8}$$

F1-Score: The F1-score is the harmonic mean of precision and recall, providing a balance between the two. It is useful when a single metric that balances both concerns is needed. This is especially true with an uneven class distribution.

$$F1 - Score = \frac{Precision\ X\ Recall}{Precision + \ Recall} \tag{9}$$

Confusion matrix

The confusion matrix in the study shows how the model classified eye images as female or male. It also broke down correct and incorrect predictions compared to the actual data.

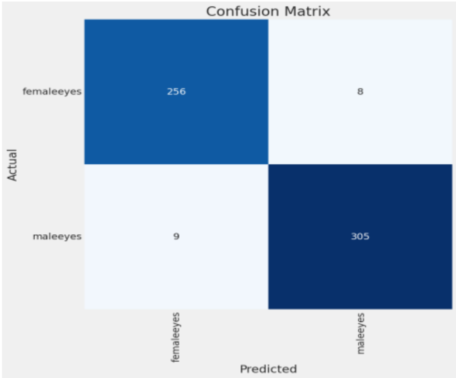

Figure 3. Confusion matrix

This confusion matrix shows how well the model classifies gender, which consisted of two groups: female eyes and male eyes. It signifies that the model correctly identified 256 samples as female eyes. However, it labelled 8 samples as female eyes, despite the opposite. For male eyes, the model accurately identified 305 samples. Yet, it made an error by classifying 9 samples as male eyes.

Model parameters

Table 3 presents the CNN model parameters used in this study. Each layer has a unique output shape and contains both trainable and non-trainable parameters. This architecture is essential for structuring and optimizing the model during training and evaluation.

Table 3. Model parameters

Layer (Type)	Output Shape	Parameter
Conv2d (Conv2d)	(None, 73, 73, 73)	896
batch_normalization (batchnormalization)	(None, 73, 73, 73)	128
max_pooling2d (maxpooling2d)	(None, 36, 36, 32)	0
conv2d_1 (conv2d)	(None, 34, 34, 34)	9,248
max_pooling2d_1 (maxpooling2d)	(None, 17, 17, 32)	0
conv2d_2 (conv2d)	(None, 15, 15, 64)	18,496
spatial_dropout2d (SpatialDropout2D)	(None, 15, 15, 64)	0
max_pooling2d_2 (MaxPooling2D)	(None, 7, 7, 64)	0
flatten_1 (Flatten)	(None, 3136)	0
dense_3 (Dense)	(None, 128)	401,536
dropout_2 (Dropout)	(None, 128)	0
dense_4 (Dense)	(None, 1)	129
Trainable parameters: 430,369		
Non-trainable parameters: 64		

This research utilized a CNN parameter for gender classification. The model started with a Conv2D layer for feature extraction. Batch normalization was followed by training stabilization. A MaxPooling2D layer reduced the spatial dimensions of the feature maps. The model added two convolutional layers with larger filters, which captured more complex features. It then used SpatialDropout2D to prevent overfitting. The features were then flattened into a vector through a Dense layer with 128 neurons, followed by a Dropout layer for regularization. The final Dense layer used a sigmoid activation function with produced outputs of a probability for gender classification (male or female). The architecture successfully learned and generalized patterns. It classified gender and prevents overfitting using dropout and batch normalization.

RESULTS AND DISCUSSIONS

This study tested KNN and CNN for gender classification using eye images with the following results and performance analysis.

The KNN classification results showed an accuracy of 81%. Table 4 below summarizes the analysis of the evaluation metrics, including precision, recall, and F1-score for each class (male and female):

Table 4. Accuracy of KNN model

Dataset	Precision	Recall	F1-score	Support
0	0.87	0.70	0.78	1078
1	0.78	0.91	0.84	1227
Accuracy			0.81	2305
Macro avg	0.82	0.80	0.81	2305
Weighted avg	0.82	0.81	0.81	2305

The k-nearest neighbors (KNN) algorithm classified gender with 81% accuracy. However, it also used precision, recall, and F1-score for a deeper analysis. For females, the precision was 0.78, meaning that 78% of predictions were correct. For males, the precision was higher at 0.87, suggesting better accuracy in identifying males. The recall for females was 0.91, indicating that 91% were correctly identified. For males, however, the recall dropped to 0.70, signifying more missed cases. The F1-score for females was 0.84, better than the male score of 0.78. The KNN model average scores included precision of 0.82, recall of 0.80, and F1 of 0.81. The model performed well across both classes, with slightly better performance for females. This suggests that the model can accurately distinguish between genders, but it is biased toward females, as shown by its higher recall and F1 scores for females. A potential anomaly was observed in the relatively lower recall for the male class. The model was precise in predicting males but missed many instances. This could stem from dataset imbalance or KNN algorithm limits. Further investigation is therefore necessary. Possible improvements include tuning hyperparameters, resampling, or using different distance metrics. In this study, the authors set up the KNN model with 16 neighbors, and used Euclidean distance as well as uniform weighting. These choices affected the classification results. The findings show a need for adjustments and suggest that combining methods might improve classification, especially for males.

In contrast, CNN achieved 93% accuracy, which was significantly better than others. Table 5 below summarizes the model's evaluation metrics.

Table 5. Accuracy of CNN model

Gender	Precision	Recall	F1-score	Support
0	0.94	0.91	0.92	1288
1	0.93	0.95	0.94	1594
Accuracy			0.93	2882
Macro avg	0.93	0.93	0.93	2882
Weighted avg	0.93	0.93	0.93	2882

A CNN model was used for gender classification with 93% accuracy and outperformed the KNN algorithm. The authors analyzed the CNN's precision, recall, and F1-score for both genders. The scores for females (class "0") were as follows: precision of 0.94, recall of 0.91, and F1 of 0.92, indicating that the model identified most females correctly with few false positives. For males (class "1"), the scores were as follows: precision of 0.93, recall of 0.95, F1-score of 0.94. These indicate excellent identification with few false negatives. The averages for both genders were 0.93, demonstrating strong, balanced performance. In this study, the CNN model achieved high accuracy and its deep structure learned complex features from images well. The convolutional layers extracted features, the pooling layers reduced size, and the dropout layers prevented overfitting. This setup beat models such as KNN in classification accuracy. The results showed few anomalies, and nothing unexpected occurred. However, the recall for females was lower than for male. This might be due to dataset biases or the model higher sensitivity to males. Males had better recall and F1 score. To fix this, exploring dataset balancing or tuning could help. In summary, the CNN model excelled in gender classification. It proved effective and reliable, showing good generalization. Future work should aim to improve the balance between classes.

Figure 4 presents the CNN model's accuracy for 50 epochs. The red line represents training accuracy, while the blue line represents validation accuracy.

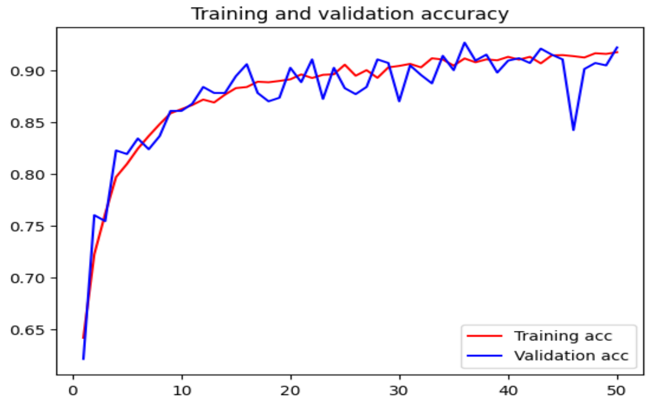

Figure 4. CNN model's accuracy comparison chart

The CNN model achieved 93% accuracy and surpassed KNN. The graph shows training and validation accuracy both nearing 0.90 at 50 epochs. This suggests minimal overfitting and good generalization to new data. The CNN excelled in identifying key features in eye images. It showed high precision and recall for both classes, indicating that it accurately predicted the positive class and identified most positive examples. With F1-scores of 0.92 for class 0 and 0.94 for class 1, the model balanced precision and recall well. This highlights CNN ability to differentiate features between classes. It proved more effective for gender classification from eye images.

Figure 5 shows a graph comparing the KNN and CNN models using precision, recall, F1-score, and total accuracy. The graph evaluates both algorithms for two classes.

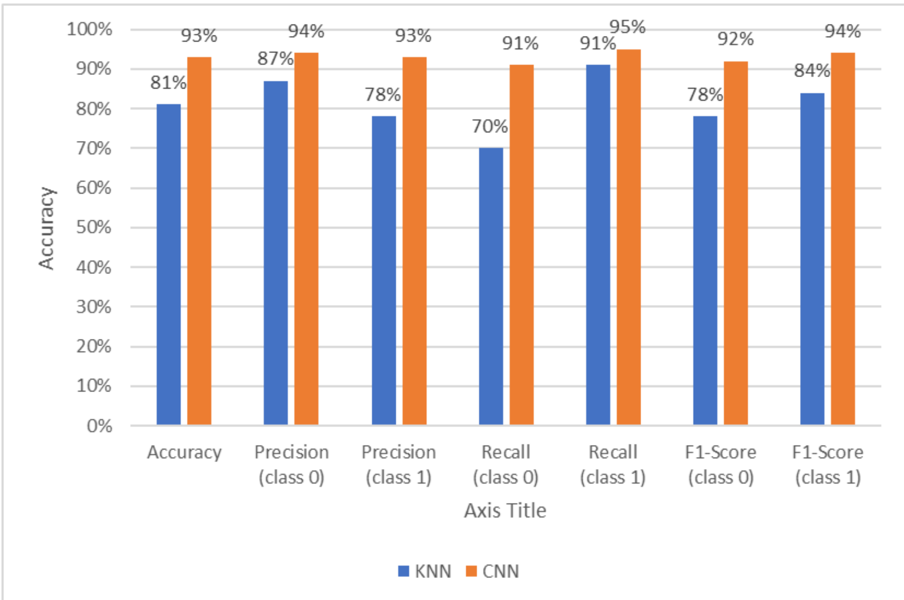

Figure 5. Comparison graphs of KNN and CNN

This study compared KNN and CNN for gender classification using iris images. It evaluated each model's accuracy, precision, recall, and F1 score. The findings enhance biometric identification, especially iris-based gender classification. The CNN model achieved 93% accuracy, surpassing the KNN model with 81% accuracy. The CNN model employed convolution layers for complex feature extraction and used batch normalization, dropout, and max-pooling to improve generalization and prevent overfitting. Meanwhile, the KNN model relied on distance metrics for class identification. It struggled with complex datasets and distinguishing gender-related iris patterns. In the KNN model, precision for males was high, but recall was low, leading to many false negatives. This issue arose from the KNN model's difficulty with high-dimensional images and specific iris features. For CNN, male recall slightly exceeded female recall, suggesting a bias. This indicates that the CNN model is better at identifying males than females.

This study features certain limitations. Its small, possibly unbalanced dataset could be improved with more diverse iris images. This would enhance the model generalizability. The KNN method, based on Euclidean distance, struggles with high-dimensional data. Trying different distance metrics or selecting better features could boost its performance. The authors tested only one CNN architecture. Its sensitivity to small class imbalances shows a need for better regularization. Future research could improve the KNN model by exploring better distance measures and feature selection. It might also combine KNN with CNN or use deeper CNN for better results. Larger, diverse datasets could reduce bias and widen applicability. Moreover, explainable AI could identify iris features linked to gender.

CONCLUSION

The CNN model outperformed the KNN model in iris-based gender classification. It captured complex visual features better. The KNN model, while simpler, struggled with high-dimensional image data. It also failed to address complex patterns effectively. Meanwhile, the CNN model showed higher accuracy and stability. This made it ideal for precise gender in biometrics. However, the CNN model faced challenges such as class imbalance and dataset limits. Therefore, techniques to reduce bias and improve models are crucial. These include data augmentation and expanding datasets. Future research should explore different CNN types and hybrid models that combine the benefits of KNN and CNN. This approach could boost classification accuracy and efficiency. Additionally, using transfer learning and larger datasets might overcome this study's limitations, leading to more reliable models in other biometric areas.

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