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Application of the nearest neigbour interpolation method and naives bayes classifier for the identification of bespectacled faces

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ABSTRACT

Facial recognition technology has rapidly advanced, but identifying individuals wearing glasses remains challenging due to altered or obscured facial features. This study addresses this issue by combining the Nearest Neighbor Interpolation Method and Naive Bayes Classification for bespectacled face identification. The method applies interpolation to enhance facial image quality, preserving critical features before classification by Naive Bayes into spectacle and non-spectacle classes. Using the Kaggle MeGlass dataset for training and testing, the approach achieved a training accuracy of 78%, a testing accuracy of 76%, and a cross-validation value of 0.70. These results indicate a significant improvement in recognizing bespectacled faces, contributing to enhanced accuracy in facial recognition systems. Despite these advancements, further improvements are possible, such as integrating more advanced models and expanding the dataset, which could lead to even greater accuracy and reliability in practical applications. This research provides a novel solution to a persistent challenge in facial recognition technology.

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Introduction

The introduction of facial recognition technology has grown rapidly in the last decade, making significant contributions in areas such as security, marketing, and interactive technology (W. Ali et al., 2021a; Zhong et al., 2021). However, facial recognition still faces significant challenges when subjects wear accessories such as glasses, which can significantly alter facial features and affect identification accuracy (Jayaraman et al., 2020; M. Wang & Deng, 2021). This study aims to overcome this problem by applying the Nearest Neighbour Interpolation method and Naive Bayes Classifier in the identification of bespectacled faces (Ahmed et al., 2023).

The issue of facial identification with glasses becomes important because glasses can cover or alter critical facial features necessary for accurate identification, thereby reducing the effectiveness of facial recognition systems (Andrejevic & Selwyn, 2020). In the context of security and authentication, for example, the inability to accurately identify someone can have serious consequences (Nguyen et al., 2022; Yaacoub et al., 2020). Therefore, this study was carried out to address these shortcomings, improving the reliability of facial recognition systems in the face of variations such as the use of glasses by subjects (Oloyede et al., 2020a).

This study aimed to solve the problem of inconsistent face identification in individuals who wear glasses by developing and integrating the Nearest Neighbour Interpolation method and Naive Bayes Classifier (R. Ali et al., 2022; Karnati et al., 2023; Malgheet et al., 2021). The research is important because it could improve security and convenience in applications that require accurate facial identification, from smartphones to entrance security systems (Dargan & Kumar, 2020; Kostka et al., 2021).

To address this issue, the study will apply an innovative approach using Nearest Neighbour interpolation to improve the quality of face data prior to classification with the Naive Bayes Classifier (Bao et al., 2020; Sharma et al., 2022). This approach is expected to improve the accuracy of facial identification by reducing distortion caused by glasses (W. Ali et al., 2021b; Hedman et al., 2022; Oloyede et al., 2020b). Kaggle's MeGlass dataset, released in 2018, will be used to train and test models, using Cross Validation evaluation metrics to assess their performance (Cerqueira et al., 2020; Xiong et al., 2020).

This research highlights some of the weaknesses of existing facial recognition methods, especially when dealing with subjects wearing glasses. Many previous studies focused on improving the resolution of facial images or mapping perturbed recognition trends and patterns, but did not specifically address the challenge of face recognition with glasses. For example, facial resolution enhancement methods that use dictionary-based interpolation algorithms only produce high-resolution facial images that are more discriminative and noise-free, but are not designed to specifically address face recognition with glasses(Rajput & Arya, 2020). Likewise, research on semantic data augmentation and face normalization from large angles does not directly address the problem of face recognition with glasses.

The specific contribution of this research is the combination of Nearest Neighbor Interpolation and Naive Bayes Classifier methods to improve the quality of facial data before the classification process, which significantly increases the accuracy of identifying faces with glasses. The combination of these two methods offers key advantages, namely reducing distortion caused by glasses and increasing the reliability of facial recognition systems in various lighting conditions and orientations. This advantage can be applied in a variety of practical applications, such as security entry systems, mobile devices that require facial identification, and other interactive applications that demand high accuracy even if the user is wearing glasses.

Facial recognition systems have evolved rapidly but face challenges when subjects wear glasses that can alter facial features and interfere with accuracy. Although efforts such as improving image resolution have been made, few researchers have focused on the issue of facial recognition with glasses. Related research is still limited and has not fully addressed this challenge. Therefore, this study developed a new approach by combining Nearest Neighbor Interpolation and Naive Bayes Classifier to identify bespectacled faces. The goal is to improve the accuracy and reliability of bespectacled facial recognition for applications that require accurate identification. This approach is expected to provide innovative solutions to challenges that have not been overcome before.

Related research (Rajput & Arya, 2020), Face resolution enhancement using functional and dictionary-based interpolation algorithm methods produces high-resolution facial images that are more discriminatory and noise-free, but does not specifically address bespectacled face recognition. Next (Ge et al., 2022), Research on impaired driving recognition using bibliometric analysis and co-occurrence networks maps trends, patterns, and methods of impaired recognition comprehensively, but does not focus on facial recognition with glasses. Then (Gunawardena et al., 2022), Eye tracking research on mobile devices using deep learning and machine learning analyzes eye tracking solutions in depth to provide insight into learning patterns and cognitive signs, but does not address bespectacled facial recognition specifically. On the other hand (Y. Wang et al., 2021), semantic data augmentation research using implicit semantic data augmentation (ISDA) improves neural network generalization performance in a variety of tasks by increasing the diversity of training data, though not specifically for bespectacled facial recognition. Last (Luan et al., 2021), Face normalization research from a large angle using Frontal View Reconstruction based GAN (FVR-GAN) synthesizes frontal facial imagery from a large viewpoint to improve facial recognition accuracy, but does not specifically address facial recognition with glasses.

By combining the Nearest Neighbour Interpolation and Naive Bayes Classifier, the study is expected to make a significant contribution to the accuracy of bespectacled face recognition systems.

Method

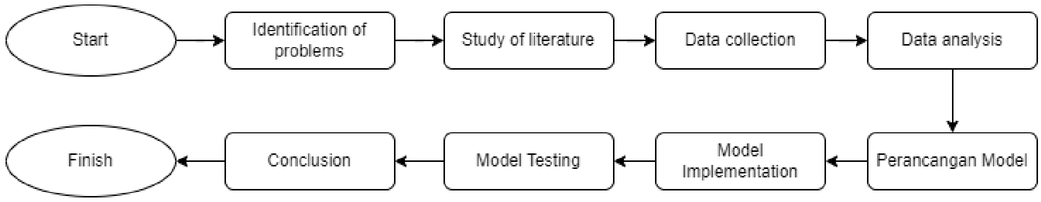


Figure 1. Research Flow

Based on Figure 1. This research begins with the problem identification stage which focuses on grouping faces based on their characteristics into two categories: glasses and non-glasses faces. Furthermore, a literature study was conducted to collect various library sources related to image processing, nearest neighbor interpolation, and naïve Bayes classifier to support theoretical understanding. A needs analysis was performed to identify the necessary components in facial image classification using the naïve Bayes classifier method. Public data from Kaggle, especially the MeGlass dataset, is taken as data analysis material to facilitate the preprocessing process before method implementation. Furthermore, the model design stage was carried out with a focus on using the nearest neighbor interpolation method and naïve Bayes classifier to measure the level of accuracy in facial image processing. The model implementation phase requires creating and executing a pre-designed model, followed by testing the model using the MeGlass dataset to detect errors that may occur so that they can be corrected immediately in this study.

Data Gathering

The dataset used is 2018 *MeGlass* which is available on the Kaggle page. The dataset consists of 47,917 images of bespectacled faces in various lighting conditions and orientations, which will be used to train and test the developed model.

Pra-Processing Data

Figure 2. Research Data

In Figure 2. The pre-processing step of the data will be taken 160 facial image data and will be divided into 2, namely 80 facial images with glasses and 80 faces without glasses, then the facial image will be pixel equalized or cropped, after cropping the facial image data will go into the preprocessing process where in this process the original facial image will be converted into grayscale and resize.

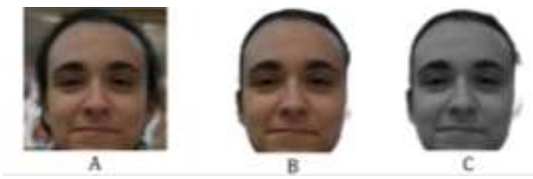


Figure 3. Image Processing

In Figure 3. The images provided illustrate the multi-stage process of preparing facial images for analysis. It starts with cropping the original image (Image A) to a size of 100 x 100 pixels, then the background is removed using the RemoveBG tool to separate the face from unnecessary details (Image B). After that, the image that has been de-background is changed to grayscale (Image C).

Algorithm Implementation

Nearest neighbor interpolation algorithm used for image pre-processing, optimizing image size and quality for the classification process. This method was chosen for its ease of implementation and effectiveness in maintaining the important characteristics of facial imagery. Naive Bayes Classifier, A probabilistic machine learning method, applied to classify images into two classes: wearing glasses and not wearing glasses. The model is trained with features resulting from data pre-processing, adapting the posterior probability of the class based on the evidence in the training data.

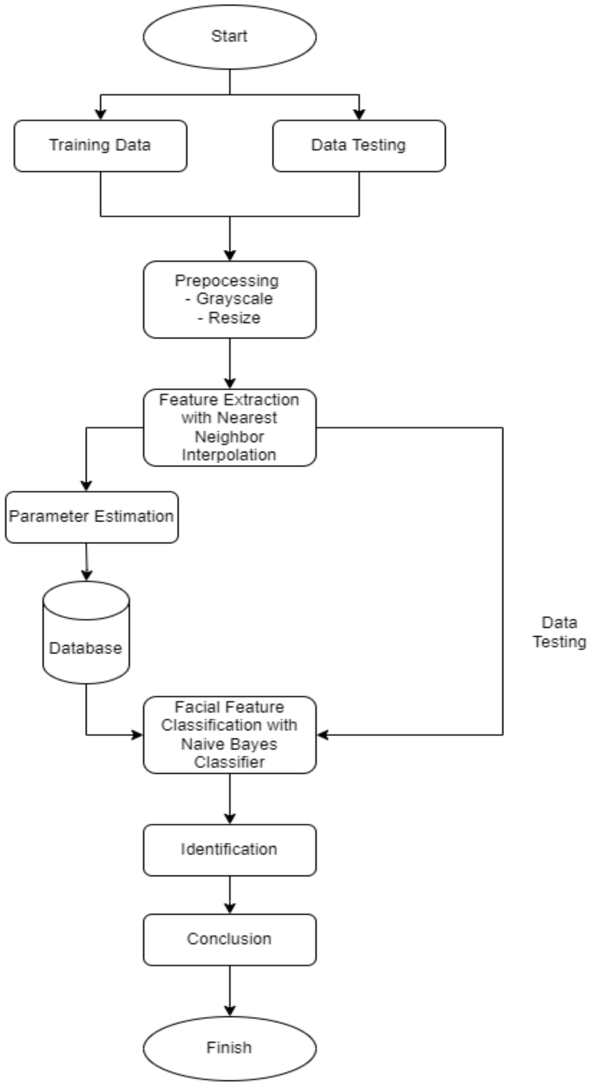


Figure 4. Method Flow

Based on Figure 4. Implementation of a model implementation involves dividing the data into two sets: 80% for training and 20% for testing. During the preprocessing stage, the original facial images are converted to grayscale and resized. Next, feature extraction is performed on the preprocessed facial images to obtain specific characteristics or features. The extracted features from the training data are then used in the classification stage. Using the Naïve Bayes classifier method, parameter estimation results are classified. Finally, in the identification stage, the classification results are utilized to produce an output based on the training process.

Model Evaluation

Data analysis involves using Cross Validation evaluation metrics to assess model performance. Classification performance is assessed based on metrics such as accuracy, and F1-score, which provide comprehensive insight into the model's effectiveness in identifying bespectacled faces.

Accuracy measures the proportion of correct positive and negative predictions across all the data tested. The formula for accuracy is given in equation 1.

$$Accuracy = \frac{Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Predictions} \quad (1)$$

Number of Correct Predictions is correct image data with prediction results, Total Number of Predictions is all total number of images that have been processed or predicted.

Precision is employed for gauging the ratio of true positive forecasts. Equation 2.

$$Precision = \frac{TP}{(TP + FP)} \quad (2)$$

If TP denotes true positives, it signifies the count of correctly predicted positive samples; TN represents true negatives, indicating the accurate prediction of negative samples; FP refers to false positives, where negative samples are incorrectly identified as positive; and FN signifies false negatives, representing positive samples erroneously predicted as negative.

Recall measures the percentage of true positive instances that are accurately detected. The formula for accuracy is given in equation 3.

$$Recall = \frac{TP}{(TP + Fn)} \quad (3)$$

TP is True Positive, that is, the number of positive samples correctly predicted by the model. FN is False Negative, i.e. the number of positive samples incorrectly predicted as negative by the model.

F1 scores balance both metrics—the accuracy formula as in equation 4.

$$F1 - Score\ = 2\ \times \frac{Precision\ \times Recall}{Precision + Recall} \quad (4)$$

Precision is the value of how accurate the model is in identifying positive examples from all positive examples predicted by the model, Recall is the value of how many positive examples the model has successfully identified from all positive examples that actually exist.

Cross-validation, on the other hand, is a technique for assessing a model's generalizability in equation 5.

$$Cross\ Validation\ = \frac{1}{k} \sum_{i=1}^{k} Accuracy_i \quad (5)$$

k is the number of folds (data division), is the accuracy of the model on the i-th fold.$Accuracy_i$.

Results and Discussions

The method used in this study is the use of the Nearest Neighbor Interpolation algorithm to resize the image and the Naive Bayes Classifier to perform the classification. The dataset used consists of images that have been grouped into two categories: glasses and non-glasses.

Figure 5. Image Processing Results

In Figure 5. There are several image sequences that have carried out a series of data processing processes aimed at preparing facial image data optimally before analysis. These steps include resizing the image to the standard size of 100 x 100 pixels, removing the background, and converting to grayscale.

Table 1. Identification Results

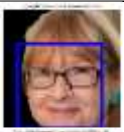
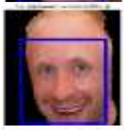
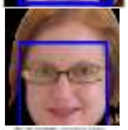
No	Image	Image Name	Type	Cross-validation accuracy	Identification Results
1		Bespectacled (27).png	Testing	0,690726	Bespectacled
2		Not Glasses (58).png	Testing	0,690726	Not Glasses
3		Bespectacled (83).png	Testing	0,690726	Bespectacled
⋮		⋮	⋮	⋮	⋮
30		Bespectacled (44).png	Testing	0,690726	Bespectacled
31		Bespectacled (42).png	Testing	0,690726	Bespectacled
32		Not Glasses (13).png	Testing	0,690726	Not Glasses

Table 2, shows the results of applying both the Nearest Neigbour Interpolation algorithm and the Naives Bayes Classifier to the identification of bespectacled faces. The table above shows 6 images that have been tested with two algorithms. Furthermore, the evaluation metrics used in this study include accuracy, recall, and F1-score. Accuracy measures the degree of congruence between prediction results and actual labels. Recall measures the model's ability to remember all positive examples, while F1-score is a harmonized measure of accuracy and recall gives an idea of the balance between the two.

From the results in the Table 2, it can be concluded that from the 32 times testing performed, as many as 25 times the predictions made by the model are correct. Thus, the precision of the model is 0.78, which means that the result of the prediction tested positive by the model is correct.

Table 2. Implementation Results

No.	Data	Accuracy	Recall	F1-Score	Cross Validations
1	Training	78%	0.78	0.78	-
2	Testing	76%	0.65	0.74	0.70

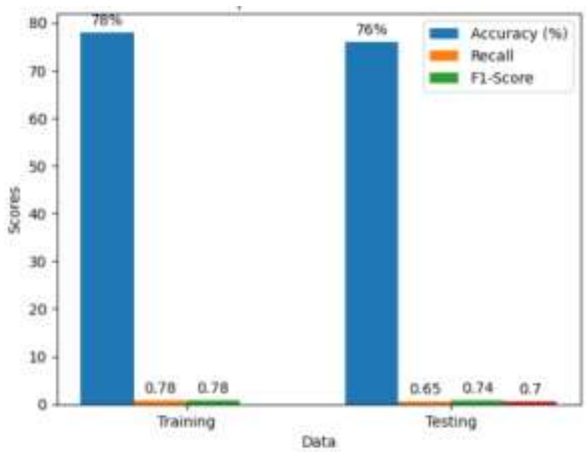


Figure 6. Performance Metrics

Tabel 3 and Figure 6. The table and graph above show the results of the implementation of the bespectacled face identification model based on training and testing data. In training data, the model achieved 78% accuracy, 0.78% recall, and 0.78 F1-Score, indicating consistent and good performance. While in the testing data, the accuracy is slightly lower at 76%, with a recall of 0.65, precision of 0.78 and F1-Score of 0.74, showing a fairly good performance but can still be improved. A cross-validation value in the test data of 0.70 indicates that the model has sufficient stability when tested on different subsets of data. Overall, the model performed well in bespectacled face identification, although there is room for further improvement. Some of the solutions that can be implemented include adding training data, data augmentation, tuning hyperparameters, better feature selection, more complex use of models, and more intensive cross-validation.

This research succeeded in filling the gaps found in previous research regarding facial recognition (Rajput & Arya, 2020). Previously, many studies focused on increasing facial resolution or using interpolation and data augmentation techniques to improve facial recognition accuracy, but none has specifically addressed the challenge of facial recognition in glasses (Luan et al., 2021), (Ge et al., 2022). This study combines the Nearest Neighbor Interpolation and Naive Bayes Classifier methods to improve the accuracy of face recognition with glasses, resulting in training accuracy of 78% and testing accuracy of 76%.

Conclusions

This research successfully developed a bespectacled face identification system using the Nearest Neighbor Interpolation method combined with Naive Bayes Classification, achieving 78% training accuracy, 76% testing accuracy, and a cross-validation value of 0.70. The system has practical implications for enhanced facial recognition in security and identification, and theoretical contributions to hybrid model applications in image processing. Despite these achievements, further improvements are possible through additional training data, data augmentation, hyperparameter tuning, better feature selection, and more complex models. Future research should explore deep learning techniques and leverage larger, more diverse datasets to enhance performance.

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