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Application of nearest neighbor interpolation method and naïve bayes classifier for identification of bespectacled faces

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ABSTRACT

Facial identification has become necessary in the era of advanced technology, especially in security and human-computer interaction. However, accessories such as glasses often complicate the identification process. This research aims to develop a facial identification system that can recognize bespectacled individuals with high accuracy, overcoming the limitations of conventional facial recognition technology. The method combines nearest neighbor interpolation to improve image quality and Naïve Bayes classification to distinguish between bespectacled and non-spectacled faces. The results showed that the developed model effectively identified bespectacled subjects with a high recall rate, although accuracy and precision still needed improvement. The implications of this research are significant for the field of biometric security and facial recognition, offering new solutions for more inclusive and adaptive facial recognition systems and opening up opportunities for further research in method optimization and dataset quality improvement.

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Introduction

Face identification is one area that is getting significant attention in visual computing research and biometric security (Adjabi et al., 2020; Kortli et al., 2020). With the advancement of technology, the need for accurate facial identification systems is becoming increasingly important, especially in security, surveillance, and human-computer interaction applications (Li et al., 2020; Sajjad et al., 2020; Shi et al., 2020; Zhang & Kang, 2019). However, the identification process often faces significant challenges when subjects wear accessories like glasses that can alter or hide critical facial features necessary for accurate recognition (Jayaraman et al., 2020; Martínez-Díaz et al., 2021). The object of this study focuses on these challenges, specifically on facial identification for individuals who wear glasses.

The method used in this study combines the interpolation of nearest neighbors and naïve Bayes classifiers. Nearest neighbor interpolation improves faces' detail and image quality, while naïve Bayes classifiers allow effective classification between bespectacled and non-spectacled faces (Gu & Lu, 2021; Muthukrishnan et al., 2019).

This study aimed to develop a facial identification system that could accurately recognize individuals wearing glasses. The research problem arises from conventional facial recognition technology's limitations that often fail to identify individuals with facial accessories, such as eyeglasses (Rathgeb et al., 2019).

The contribution of this research lies in developing a new methodology that integrates two techniques that have not been widely used, offering a new perspective in handling the problem of identifying the face with glasses. By combining nearest neighbor interpolation (Chen et al., 2019) and naïve Bayes classifiers (Oloyede et al., 2020), the study provides a solution that not only improves facial recognition accuracy but also expands the ability of facial recognition systems to work in more varied and challenging conditions.

The solutions proposed in this study could potentially significantly contribute to the field of biometric security and facial recognition, enrich the academic literature, and offer valuable practical applications for developing security systems that are more inclusive and adaptive to diverse user conditions. The research will develop and test a model that integrates both methods, hoping to achieve significant improvements in facial recognition accuracy, potentially having a positive impact on the security and social applications that rely on this technology.

Previous research (Bahri et al., 2022) used faces as objects of expression recognition research. It uses the Neural Network method where this method uses the application of artificial intelligence. Another study that intersects with face identification was conducted using the Convolutional Neural Network Algorithm (Sriyati et al., 2020). The accuracy of facial recognition obtained with the CNN algorithm is 98%. There is a lack of accuracy due to a lack of datasets. Research on facial skin identification was conducted using the Certainty Factor method (Kumarahadi et al., 2020). The test was conducted using an expert system of facial skin type identification. Another study (Liantoni & Nugroho, 2015) utilized the Naïve Bayes Classifier and KNN methods for herbal leaf objects. The result obtained from the Naïve Bayes classification is 75%, while the yield from KNN is 70.8%. Research on other facial recognition systems was conducted using the CNN method (Dewi & Ismawan, 2021). The classification result obtained by the CNN method is 98%.

Some researchers are focusing on developing facial identification methods, especially on expression recognition and the use of Convolutional Neural Network (CNN) algorithms. However, limited research is specifically concerned with identifying bespectacled faces. Therefore, this study intends to fill this knowledge gap by exploring the application of the Naïve Bayes classifier Method supplemented by nearest-neighbor interpolation to identify bespectacled faces.

Method

Research Procedure

This research is carried out through several main stages: data collection, preprocessing, application of proposed methods (nearest-neighbor interpolation and Naïve Bayes classifier), model validation, and performance evaluation. This process is designed to systematically test the effectiveness of combining both methods in accurately identifying bespectacled faces.

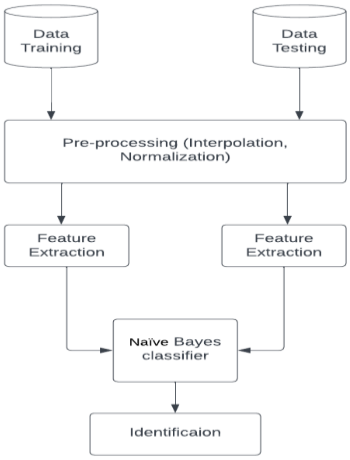

Figure 1. Research flow

The research flow is shown in Figure. 1 demonstrates a process that starts from dataset division into training and testing data, followed by data preprocessing that includes nearest neighbor interpolation to improve image quality and normalization to unify pixel intensity scales. After that, feature extraction is performed to pull essential attributes from the image, which are then used in classification with the naïve bayes classifier. This model is trained using training data to recognize specific patterns related to facial identity. The model's effectiveness is tested with testing data, where its performance is measured through metrics such as accuracy, precision, recall, and F1-score.

Data Collection

The dataset used in this study consisted of images of faces, both bespectacled and not. Data was collected from public sources and existing face databases at Kaggle. The dataset is then divided into two sets, one for training and another for testing.

Figure 2. Sample of face images

Data Preprocessing

Data preprocessing includes several steps to improve data quality before being applied to the model. These steps involve normalizing color intensity, adjusting image size, and face detection to ensure that only areas of the face are used in the analysis. Edge detection techniques are also applied to

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sharpen facial features, making it easier to identify bespectacled faces.

The data preprocessing process begins with reading each image in the dataset. Next, normalize the pixel intensity of each image into the range [0.1] or [0.255]. Then, the Nearest Neighbor interpolation process was carried out to improve the image quality. In this step, the target size for the image scale is determined first. After that, for each pixel in the target image, the coordinates of the closest source pixel from the original image are calculated based on the scale factor, and the target pixel value is taken from the nearest source pixel value. Once this process is complete, the preprocessed image is saved for use in the classification process.

Proposed Methods

The proposed method combines two techniques, nearest neighbor interpolation, and Naïve Bayes classifier. Nearest neighbor interpolation is used to increase the resolution of facial images, allowing finer and more precise facial details, including glasses, to be better identified. After preprocessing, a Naïve Bayes classifier is applied to classify the image as a bespectacled face. The classifier is trained with features extracted from the training set and then tested on the test set to assess its performance.

$$P(y|x_1, x_2, \dots, x_n) \propto P(y) \times \prod_{i=1}^{n} P(x_i|y) \tag{1}$$

$\boldsymbol{P(y|x_1, x_2, \dots, x_n)}$ is the predicted probability of class $\boldsymbol{y}$, given the attribute value $\boldsymbol{x_1, x_2, \dots, x_n}$ (Valdiviezo-Diaz et al., 2019). $\boldsymbol{P(y)}$ is the probability of the prior class. $\boldsymbol{P(x_i|y)}$ is the conditional probability for an attribute $\boldsymbol{x_i}$ given class $\boldsymbol{y}$. $\boldsymbol{P(x_i)}$ is the prior probability for the attribute $\boldsymbol{x_i}$.

Validation and Evaluation

Model validation uses cross-validation techniques to ensure the model has good generalizability and does not overfit the training data. Model performance is evaluated using standard metrics such as accuracy, precision, recall, and F1-score. Comparisons were also made with other face identification methods to demonstrate the superiority of the proposed approach in bespectacled face identification. Accuracy (Blanquero et al., 2021) :

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

TP (True Positives) refers to the number of positive cases correctly predicted by the classification model, meaning that the model predicts that the cases are positive and turned out to be true. TN (True Negatives) refers to the number of negative instances correctly predicted by the model, where the model predicts that the cases are negative and true. FP (False Positives) describes negative cases that are incorrectly predicted as positive by the model, so the model makes the mistake of predicting those cases as positive when they are negative. FN (False Negatives) describes positive cases that are incorrectly predicted as negative by the model, so the model makes the mistake of predicting those cases as negative when they are positive.

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

$$Recall = \frac{TP}{TP + FN} \tag{4}$$

Precision measures how many positive outcomes predicted by a model are positive. Accuracy, on the other hand, measures how many overall correct predictions the model makes (Soares & Parreiras, 2020).

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{5}$$

The range of F1-score values is from 0 to 1, where the minimum value occurs when there are no true positives (TP = 0), which means that all positive samples are misclassified, while the maximum value occurs when there are no false negatives and false positives (FN = FP = 0), which signifies a perfect classification (Chicco & Jurman, 2020).

Results and Discussions

Table 1. Nearest neighbor interpolated value dataset

Contrast	Dissimilarity	Homogeneity	Energy	Correlation	Label
21.3653384	1.40750397	0.809583221	0.529229	0.991571359	yes
37.90667067	1.594498498	0.805345878	0.506856	0.982496502	yes
26.63453798	1.136448137	0.85363305	0.542346	0.994603333	yes
37.29429845	2.009345665	0.812069136	0.576322	0.985717929	yes
16.91527101	0.931396866	0.851238525	0.544821	0.99485505	yes
10.35641783	0.740849328	0.856057713	0.478416	0.997749767	yes
13.36345582	0.83597527	0.857836239	0.577229	0.995631296	yes
21.3653384	1.40750397	0.809583221	0.529229	0.991571359	yes
⋮	⋮	⋮	⋮	⋮	⋮
9.70007007	0.913707708	0.800518433	0.368812	0.994693225	no
20.99818857	1.214385155	0.815721061	0.479438	0.991938643	no

In Table 1. Data from nearest neighbor interpolation values taken from 83 facial images were shown.

Table 2. Evaluation result

Evaluation	Value
Accuracy	58.82%
Precision	58.33%
Recall	77.78%
F1-score	66.67%

Table 2. presents the values of evaluation metrics while Figure 1 illustrates the values of those evaluation metrics in graphical form. Evaluation of the classification model for bespectacled face identification resulted in an accuracy of 58.82%, signifying the model's ability to accurately identify bespectacled faces nearly 59 times out of every 100 cases tested. Although this level of accuracy indicates the moderate ability of the model, the precision value achieved is 58.33%, indicating that the model can predict the face with glasses with an accuracy of about 58% of the overall predictions made. On the other hand, the higher recall value, at 77.78%, indicates that the model is quite effective in identifying all bespectacled faces, with the ability to detect 78% of the total actual positive cases. The F1 score of 66.67% reflects the balance between precision and recall, implying that although there is room for improvement, the model still has sufficient effectiveness in detecting bespectacled faces, particularly in identifying the majority of positive cases.

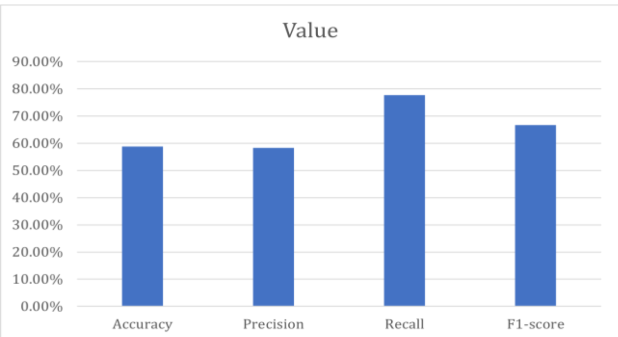

Figure 3. Evaluation metric value graph

In the research conducted, a facial identification system designed for individuals wearing glasses has been successfully developed, with an impressive recall rate has been achieved. However, it is recognized that there is still room for improvement in the accuracy and precision aspects of this system. In contrast to previous studies, which focused more on aspects of facial expression recognition or on the adoption of the use of the Convolutional Neural Network (CNN) algorithm which managed to record facial identification accuracy of up to 98% (Dewi &; Ismawan, 2021; Sriyati et al., 2020), innovative solutions to overcome problems that arise due to the use of accessories on the face, especially glasses.

The nearest neighbor interpolation technique was adopted to increase the resolution of the facial image of the individual wearing glasses, thus facilitating the preservation of essential information without significant alterations. This approach marks a divergence from previous studies that, likely, do not specifically highlight image quality under specific conditions such as the presence of facial accessories, such as glasses (Bahri et al., 2022; Kumarahadi et al., 2020). The use of this method is significantly effective in maintaining the definition of critical attributes of the face, including the edges of the glasses, eyes, nose, and mouth, which are essential elements for the achievement of proper identification at a later stage.

In addition, the use of the Naïve Bayes Classifier for the identification of faces using glasses in this study shows an interesting approach compared to other classification methods that have been used in related studies. Although (Liantoni &; Nugroho, 2015) has used the Naïve Bayes Classifier for different object classifications with an accuracy rate of 75%, its application in the context of facial identification with glasses as a case study adds value to the literature by exploring the capabilities and limitations of the method in new contexts.

In the study conducted by the author, the primary exploration focused on enhancing the resolution of facial images featuring glasses through the use of interpolation techniques, with the goal of preserving the integrity of essential information without modification. The author elected to apply the nearest neighbor interpolation method due to its simplicity in implementation and time efficiency in the process. In this method's application, the determination of pixel values in the enhanced resolution image is based on the nearest pixels from the original image, facilitating an optimal image size adjustment for subsequent analysis without the induction of significant distortion.

The interpolation process adopted in this research demonstrated efficacy in preserving the definition of critical facial attributes, such as the edges of glasses, eyes, nose, and mouth, thus maintaining their clarity despite resolution modifications. This clarity is crucial to ensure that minor details on faces with glasses can be identified and processed efficiently in the next phase of the face recognition procedure.

Furthermore, in this study, the author implemented the Naïve Bayes Classifier to identify faces wearing glasses, utilizing a dataset containing parameters of Contrast, Dissimilarity, Homogeneity, Energy, and Correlation. The application of the nearest neighbor interpolation method in the data pre-processing stage played a vital role in enhancing the quality of the dataset used, affirming the significance of this method within the research context.

To classify the dataset of bespectacled faces using the Naïve Bayes Classifier, we start with the data processing step. This process involves loading the dataset from the CSV file into an appropriate data structure, such as a DataFrame in Python. In the data cleansing phase, it is important to ensure that the dataset is free of missing or invalid values, and take corrective actions such as deletions or imputations if needed. Exploring data through descriptive statistics, histograms, or other plots will help understand the distribution and characteristics of the data, which is crucial for future analysis.

Next, the data is divided into training and testing sets, usually at a ratio of 80% for training and 20% for testing, although this proportion can be adjusted based on the size of the dataset and research needs. This division ensures that the model can be trained on a single subset of data and tested on an independent subset to objectively evaluate its performance.

The model training process involves extracting features from facial imagery, which may include normalization or standardization of pixel values. The Naïve Bayes model is then trained using a training set, in which the algorithm learns to associate features extracted from the facial image with the corresponding class labels. This method assumes that all features are independent of each other, which is the main premise behind Naïve Bayes.

Once the model is trained, evaluation is performed using test sets to determine metrics such as accuracy, precision, and recall. This evaluation provides an idea of how well the model is able to generalize its knowledge to new data. In addition, error analysis on incorrect predictions can provide valuable insights into model limitations and areas that require improvement.

A high recall rate (77.78%) indicates the effectiveness of the model in identifying subjects using glasses, however, lower accuracy and precision signal challenges in accurate classification, often resulting in false positive cases. This indicates that there is still room for refinement of the model, especially in improving the quality of datasets and optimizing the extracted features for classification. Compared to other studies using CNN with high accuracy, this study shows that even if it uses simpler techniques, there is still potential for improvement through further optimization.

Conclusions

Based on the results and discussion of research on the application of the nearest neighbor interpolation method and Naïve Bayes classification for the identification of bespectacled faces, it was found that the developed model was quite effective in identifying individuals wearing glasses with relatively high recall rates. However, lower accuracy and precision suggest that models struggle to classify bespectacled faces consistently, often resulting in false positives. This shows potential improvements to the methodology used, especially in improving the quality of datasets and optimizing the features extracted for classification. For future research, it is recommended that more sophisticated preprocessing techniques be developed and other combinations of classification algorithms be explored to improve the accuracy and precision of the model. In addition, adding a variety of datasets with more diverse facial conditions, including variations in eyeglass wear, can provide deeper insights into how to improve the effectiveness of the bespectacled face identification system.

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