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Violation Detection on Traffic Light Area Based on Image Classification Using Dimensionality Reduction and Deep Learning

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Abstract: The smart city concept is closely related to efficient traffic management, especially using technology to improve safety and smooth traffic flow, including at traffic lights. In this context, traffic light integration into a smart city system uses sensors, surveillance cameras, and intelligent algorithms to adaptively manage traffic based on vehicle volume and real-time traffic conditions. The CCTV already installed in several junction road at Bandung City, Indonesia. Image classification using deep learning is an essential and rapidly growing application in artificial intelligence. When the number of images in the dataset collected from CCTV gets larger, the total dimension of the data will also increase significantly. The large dimension of image datasets makes the data analysis and processing process more complex and requires extensive computational resources. To reduce computational resource, dimensionality reduction using Principal Component Analysis (PCA) can handle high-dimensional data. PCA is used to process and analyze image datasets efficiently. We proposed combination of deep learning and PCA to solve classification problem to high dimensional traffic image dataset. Experimental result showed that the non-PCA deep learning model achieved an accuracy of 73.11%, while the deep learning model with PCA achieved an accuracy of 72.73%. In other hand, the combination of deep learning and PCA showed a much shorter training time of only 2.95 seconds compared to the non-PCA deep learning model, which took 80.43 seconds.

Keywords: CCTV, Image Classification, deep learning, PCA, accuracy, computation time.

1. Introduction

The rapid increase in the number of new vehicles on the road is leading to significant congestion, which often results in more frequent traffic rule violations. This, in turn, contributes to a higher rate of road accidents. Computer vision-based traffic violation detection systems are highly effective in reducing these violations by monitoring, tracking, and penalizing offenders.

Initially, traffic monitoring relied on human traffic officers stationed at each junction, requiring constant human presence and resources. However, as the number of vehicles increased, this approach became increasingly impractical. This led to the development of trigger-based traffic detection systems, designed primarily to detect a single type of violation—speeding. These systems were expensive, could only be installed at specific points on the road, and were easy for drivers to avoid. There was a growing need for a system that could operate 24/7, require minimal or no human intervention, and accurately identify multiple types of violations. This necessity gave rise to traffic violation detection using computer vision. These systems leverage advanced computer vision technologies, integrating image processing, artificial intelligence, and deep learning to monitor and enforce traffic laws more effectively.

a) Cross border violation occurs

b) violation does not occur

Fig. 1. The differences between violation and non-violation images

This system detects objects by identifying instances of semantic objects and classes in digital images and videos. The video footage captured from cameras can be repurposed for various other applications, significantly reducing operational costs. Additionally, the monitoring infrastructure can be extended beyond urban areas to rural roads and highways without incurring extra expenses. This approach saves time and allows traffic police personnel to focus on more productive tasks. Computer vision-based detection operates on the principles of vehicle classification, environmental awareness, and traffic violation detection. This research based on image classification on the traffic image dataset which taken from CCTV. We capture the images from CCTV video, capture the image into two categories: violate and non-violate. Fig. 1 is the sample of dataset; we carefully select and treats it as binary class classification problem.

2. Related Work

The authors propose using Gaussian Mixture Model (GMM) and Automatic Number Plate Recognition (ANPR) to detect motor vehicle tax violations through type and plate number identification [1]. This research proposes developing an automated system that uses computer vision to control these violations. The system detects vehicle violations and identifies the registration numbers of offending vehicles to send alerts to the host [2]. The process of vehicle detection involves searching for vehicle contours using the BLOB method. Furthermore, vehicle tracking is performed using the Mean Shift Algorithm to recognize road marking violations. A border is created as a reference in the CCTV video using image processing techniques [3]. Detecting multiple vehicle violations provides a comprehensive understanding of the concepts and technology used in developing a traffic signal violation detection system with computer vision, based on YOLOv3 [4]. Daubechies 8 wavelet transform was employed to extract features from the upper part of the segmented image, specifically the motorcycle. These features were then used as input for training a classifier based on SVM (Support Vector Machine) [5].

PCA has been widely applied to remove noise in digital signal processing, image recognition, and in solving classification issues [6] [7] [8] [9]. Research focuses on developing deep learning models using convolutional neural networks (CNNs) for the classification of fish species based on images [10]. Conducting a comprehensive study on dimensionality reduction (DR) techniques, we propose a face recognition method utilizing PCA transformation. Experiments are conducted using the Olivetti Research Laboratory (ORL) and Yale face databases [11]. Feature selection and extraction, as part of dimensionality reduction, decrease the computation time of machine learning techniques [12].

This research purpose to improve the efficiency of training time in processing traffic CCTV image data. Reducing training time of image dataset provides significant benefits in developing advanced and effective traffic surveillance solutions. Combining deep learning technology and preprocessing strategies such as PCA is an essential step in optimally utilizing the potential of CCTV image data to support a modern and responsive traffic surveillance and management system.

3. Methodology

Image classification using deep learning is an essential and rapidly growing application in artificial intelligence. Deep learning uses artificial neural networks of many layers to learn autonomously from the given image data. This process involves extracting complex features from the image, which are then used to recognize and classify objects in the image.

In image classification, deep learning enables computers to understand the visual content of images and identify objects, humans, animals, or other objects with a high degree of accuracy. This method has been applied in various fields, such as face recognition, medical detection, security surveillance, and autonomous navigation.

Overall, deep learning image classification significantly contributes to developing technologies that can understand and interact with the visual world more similarly to human capabilities. As deep learning technology continues to develop, we can utilize it for various practical applications in everyday life, including in the context of smart cities, to improve surveillance and management of urban environments more efficiently.

PCA (Principal Component Analysis) is a technique used in statistical analysis and data processing to reduce the dimensionality of complex data sets to lower dimensions. The main objective of PCA is to identify significant patterns or structures in the data by projecting the original data onto a smaller dimensional space called the principal component space.

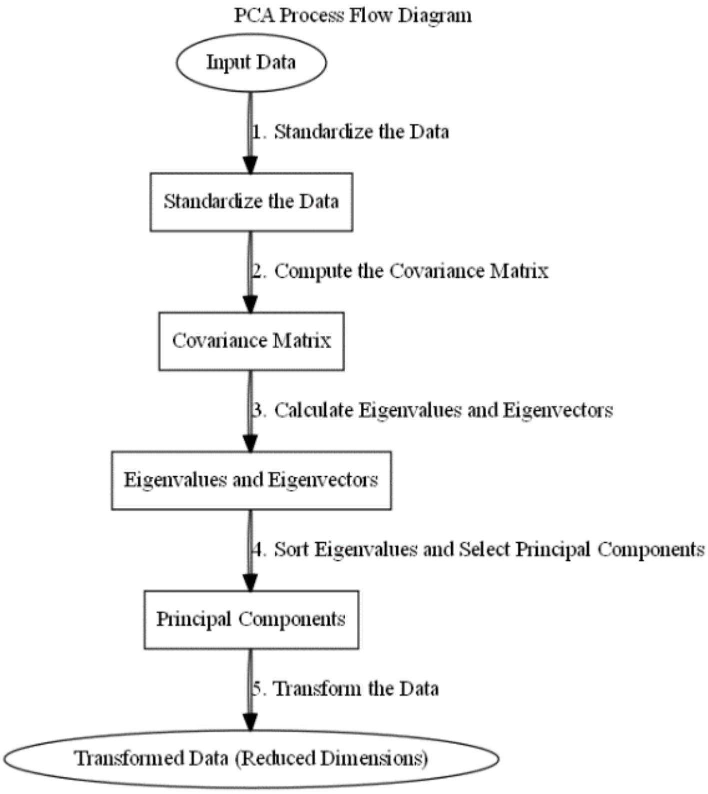


Fig. 2. Step-by-step process of PCA

The flow diagram of PCA (Principal Component Analysis) is shown in Fig. 2. The PCA (Principal Component Analysis) flow diagram illustrates the step-by-step process of reducing the dimensionality of a dataset. It begins with the Input Data, which is first standardized to ensure each feature has a mean of zero and a standard deviation of one. This standardized data is then used to compute the Covariance Matrix, capturing how the features vary together. From the covariance matrix, the Eigenvalues and Eigenvectors are calculated to determine the principal components, which represent the directions of maximum variance in the data. The eigenvalues are sorted, and the top components are selected to form the Principal Components. Finally, the original data is projected onto these principal components, resulting in the Transformed

Data with reduced dimensions, capturing most of the original variance in a more compact form. This process enables efficient data analysis and visualization by focusing on the most significant features.

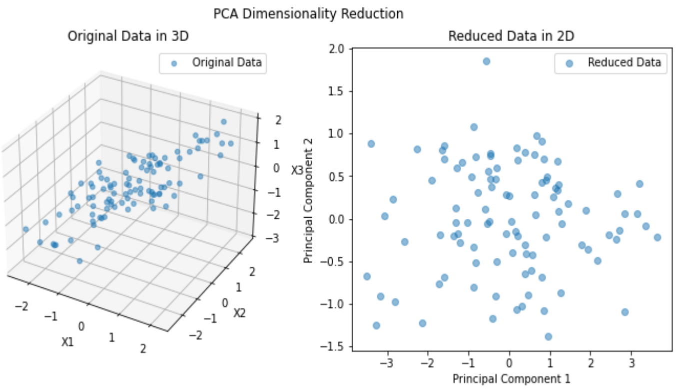


Fig. 3. Sample of PCA dimensionality reduction

Fig. 3 shows the data points in a 3D space, representing the high-dimensional input data. PCA is applied to the data to find the principal components, which are the directions of maximum variance. In the code, this is done using PCA(n_components=2) to reduce the data to 2 dimensions. The transformed data points are plotted in a 2D space, representing the lower-dimensional output after PCA has been applied.

PCA has many applications, including dimensionality reduction in image data, pattern recognition, genetic data analysis, and data compression. In various fields, PCA helps to identify the most critical features in data and simplify their complexity, thus facilitating more effective and efficient analysis.

Dimension reduction on digital image

A digital image can be depicted as a collection of pixels organized in a two-dimensional matrix, as illustrated in this picture. For a colored image, these pixels have floating point values, while for a grayscale image, the pixel values are discrete.

$$f(x)=\begin{bmatrix} f(0,0) & \cdots & f(0,m-1) \\ \vdots & \ddots & \vdots \\ f(n-1,0) & \cdots & f(n-1,m-1) \end{bmatrix} \quad (1)$$

where x and y represent the coordinates of the pixels in the image, and f(x,y) indicates the corresponding color or gray level depending on the value type. Generally, the process of image dimension reduction using PCA is divided into four main steps: image normalization, calculating the covariance matrix of the image data, determining the eigenvectors and eigenvalues of the covariance matrix, and finally, transforming the image data into a new basis.

TRUE: YES
PREDICT: YES
a) Violation does not occur and deep learning prediction is correct

TRUE:NO
PREDICT: NO
b) Violation occur and deep learning prediction is wrong

Fig. 4. Image classification prediction result based on deep learning

Image datasets for image classification are examples of data with large dimensions because each image is represented as a matrix of high-resolution pixels. The dimension of an image dataset is affected by several factors, including the image resolution (the number of horizontal and vertical pixels), the number of color channels (for example, RGB has 3 channels), and the number of images in the dataset. For example, a high-resolution image such as 1920x1080 will have a total of 2,073,600 pixels (or more, depending on the number of color channels), resulting in a very long feature vector for each image.

Fig. 4 shows two images of traffic condition, captured by CCTV near traffic light. Image classification using Deep Learning can predict image label by using machine learning model from previously trained dataset.

Data was collected using a Python program to capture images via screen capture from CCTV footage during a predetermined period. The data collection process took place from May to October 2023. We utilized a dataset consisting of 800 training examples to develop a classification model. The dataset is evenly divided into two categories: 400 instances representing occurrences of violations and 400 instances representing non-violations. This balanced dataset allows the model to learn equally from both classes, improving its ability to accurately differentiate between violations and non-violations.

Accuracy is one of the most commonly used metrics to measure the performance of deep learning models in classification tasks. Accuracy is calculated as the ratio of correct predictions (positive and negative) compared to the total number of predictions made by the model on all test data. In the context of classification, accuracy gives an idea of the extent to which the model can make correct predictions.

Understanding accuracy as a performance metric of deep learning models is an important first step in model evaluation. However, to gain a more holistic understanding of model performance, it is highly recommended that accuracy be combined with other metrics that suit the needs of the classification task.

Testing the performance of deep learning with and without PCA (Principal Component Analysis) is an important step in understanding the impact of dimensionality reduction on model performance. Non-PCA deep learning uses image data in its whole dimension (e.g., a high-resolution pixel matrix). In contrast, deep learning with PCA reduces the dimensionality of the data by selecting the most meaningful principal components.

4. Result and Discussion

4.1. Result

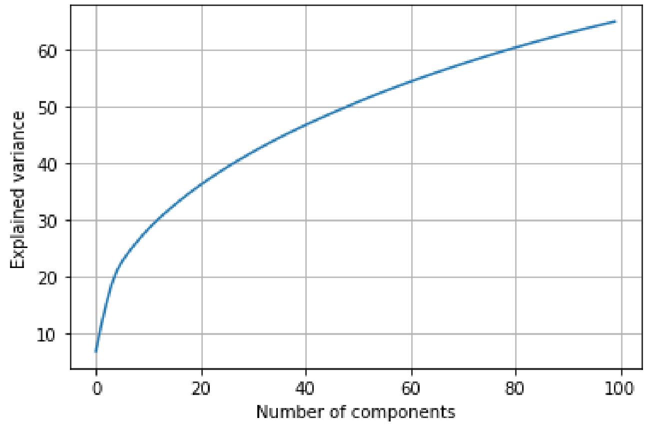


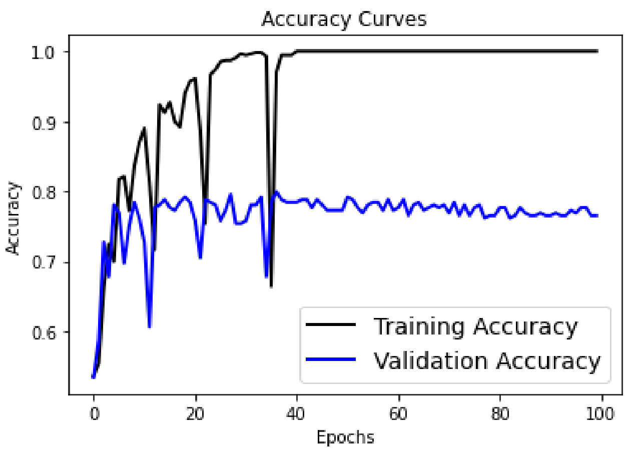
Fig. 5. Comparation between number of component and explained variance

Explained Variance Ratio is the ratio of the variance captured by each principal component to the total variance in the data as shown by Fig. 5. It provides an indication of the importance of each principal component. The sum of the explained variance ratios for all principal components will be equal to 1 (or 100% when expressed as a percentage). A good criterion for determining the number of principal components to retain in PCA using the "explained variance ratio" is to choose several components that capture a sufficiently high proportion of the total variance in the data. We choose n_components=30 as parameter input to PCA. It indicates that the experiment reduced the dimensionality of data to 30 principal components. Number of component 30 holds only 43% of the information from whole features of dataset (ration of variance (eigenvalue / total eigenvalues). PCA will find the 30 directions (components) that capture the most variance in the data and project the original data onto this 30-dimensional space.

The test results show that the deep learning model without using PCA (Principal Component Analysis) has a slightly higher accuracy than the PCA model. The non-PCA deep learning model achieved an accuracy of 73.11%, while the deep learning model with PCA achieved an accuracy of

72.73%. We cannot show the PCA Deep learning based image because only 43% of the total features is used, therefore it is hard to reconstruct images similarly deep learning method does. In the other hand. The slight difference in accuracy result suggests that dimensionality reduction with PCA may not improve model performance for image classification tasks in the context of this test.

The test results show that the training process of the deep learning model using PCA (Principal Component Analysis) takes much less time than the deep learning model without PCA. The deep learning model with PCA completed training in 2.95 seconds, while the non-PCA deep learning model took 80.43 seconds. Although the non-PCA model has a slightly higher accuracy (73.11%) than the PCA model (72.73%), as previously observed, this difference should be considered in the context of time efficiency. Using PCA for dimensionality reduction provides significant advantages in reducing the time required to train deep learning models.



Time efficiency in training deep learning models is a critical factor to consider, especially in applications where training time directly impacts system productivity and responsiveness. Test results show that using PCA (Principal Component Analysis) for dimension reduction before training can provide significant gains in terms of time efficiency.

In this context, the combination of deep learning and PCA showed a much shorter training time of only 2.95 seconds compared to the non-PCA deep learning model, which took 80.43 seconds. Although the accuracy of the PCA model (72.73%) is slightly lower than that of the non-PCA model (73.11%), this difference should be assessed considering the substantial time efficiency gains.

4.2. Discussion

While accuracy provides valuable information about the model's overall performance, it is essential to consider the context and characteristics of the data used. Accuracy can be a good indication if the classes in the dataset are balanced, i.e., the proportion between positive and negative classes is relatively equal. However, if the dataset is unbalanced (for example, there are very few minority classes), the accuracy may be unrepresentative.

Therefore, in some cases, it is important to consider other metrics such as precision, recall, and F1-score to gain a more comprehensive understanding of the model's performance. Precision measures how many positive predictions were correct, while recall measures how many overall positive classes were correctly predicted by the model. F1-score is the harmonic mean of precision and recall, providing a single value that combines both metrics.

Time efficiency in training deep learning models has direct implications for developing responsive and adaptive systems, especially in scenarios where model training needs to be done periodically or with large volumes of data. By utilizing PCA for dimensionality reduction, users can save training time without significantly sacrificing performance, which can improve overall productivity and efficiency in implementing deep learning-based solutions.

Using PCA before training a deep learning model can have several benefits. Firstly, PCA can reduce redundancy in image data, allowing deep-learning models to learn from more important feature representations. Combination deep-learning and PCA can lead to more efficient and stable models, especially when dealing with high-dimensional datasets.

However, using PCA may also prevent valuable information from being lost in the dimensionality reduction process. Therefore, it is important to comprehensively test the performance of deep learning models with and without PCA. This test can compare performance metrics such as accuracy between these two approaches.

By performing this comparison, we can evaluate whether the use of PCA increases or decreases the performance of deep learning models for image classification tasks. The results of this test can provide valuable insights into choosing the right preprocessing strategy for a particular dataset and can help develop more effective and efficient deep-learning models.

5. Conclusion

In conclusion, selecting preprocessing methods such as PCA can be an appropriate strategy to achieve a balance between model accuracy and training time efficiency. This shows the importance of considering time efficiency in the development and application of deep learning models for practical applications.

Training time efficiency in the context of traffic CCTV image data is not just a technical consideration but a critical factor in ensuring the responsiveness and reliability of traffic surveillance systems. With the large volume of image data generated by CCTV cameras, the training process of deep learning models must be done efficiently to produce models that can recognize and classify objects quickly and accurately, thereby enhancing the effectiveness of traffic surveillance.

The application of PCA (Principal Component Analysis) in preprocessing image data from traffic CCTV can be an effective strategy to reduce data dimensionality and speed up model training time. Dimensionality reduction with PCA can help in removing redundant and unimportant information from image data, thus speeding up the training process of deep learning models without significantly sacrificing performance.

With more efficient training time, the trained deep learning models can be used for real-time traffic analysis, detecting suspicious patterns, vehicles, or behaviors quickly and responsively. This is crucial in the implementation of an efficient and adaptive traffic surveillance system, which can help improve the safety and smooth flow of traffic in a particular city or area.

Thus, using PCA to improve the efficiency of training time in processing traffic CCTV image data can provide significant benefits in developing advanced and effective traffic surveillance solutions. Combining deep learning technology and preprocessing strategies such as PCA is an essential step in optimally utilizing the potential of CCTV image data to support a modern and responsive traffic surveillance and management system.

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