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Research article

Principal Component Analysis on Convolutional Neural Network Using Transfer Learning Method for Image Classification of Cifar-10 Dataset

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ABSTRACT

The current era was defined by an overwhelming abundance of information, including multimedia data such as audio, images, and videos. However, with such an enormous amount of image data available, accurately and efficiently selecting the necessary images poses a significant challenge. To address this, image classification has emerged as a viable solution for organizing and managing large volumes of image data, thereby mitigating the issue of cluttered image datasets. One of the most popular algorithms for image classification is the Convolutional Neural Network (CNN), which reduces the complexity of network structure and parameters by leveraging local receptive fields, weight sharing, and pooling operations. CNN is a type of artificial neural network specifically designed to process grid-like data, such as images, using convolutional layers to automatically detect local features. Nonetheless, CNN faces several challenges, such as gradient diffusion, large dataset requirements, and slow training processes. To overcome these issues, Transfer Learning has been widely adopted in CNN-based image classification, and Principal Component Analysis (PCA) has been employed to accelerate the training process. PCA is a technique used to reduce data dimensionality by identifying the principal components that account for most of the variance in the data. This study tested the efficacy of PCA-based CNN architecture using the Transfer Learning method on the Cifar-10 dataset. The results demonstrated that the PCA-based CNN architecture achieved the highest accuracy, with a testing accuracy rate of 0.8982 (89%).

1. Introduction

In this age of information, we are inundated with an overwhelming amount of multimedia data, including audio, images, and videos, in addition to text. The sheer volume of image data available poses a significant challenge in accurately selecting the necessary images. While people desire more data for comprehensive information, it has become increasingly difficult to retrieve image data accurately and quickly from vast collections. To address this issue, image classification has emerged as a viable solution for organizing and managing large volumes of image data, thereby mitigating the problem of cluttered datasets. Image classification serves as an effective tool for handling and organizing image data and can resolve issues with data clutter. By adopting image classification, individuals can accurately and quickly find the required images, addressing the challenges posed by an overwhelming abundance of image data [1].

The limitations in access to comprehensive data distribution and the lack of information about available data have led researchers to evaluate model performance on separate testing sets. The mismatch between the model and the data poses a problem when researchers design models that perform well on specific testing sets but fail to generalize to new data. The transparent creation process

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of CIFAR-10 data makes it highly suitable for this research. The creation process of CIFAR-10 was well documented by [2], So that the entire data structure can be visualized, making it easier for researchers to see the data distribution.

On the other hand, CIFAR-10 presents a complex classification problem. These 32x32 pixel images do not contain enough information, making it difficult to perform object detection or clear image recognition for most research purposes [3]. Therefore, feature extraction is necessary to address the problem of information deficiency caused by the limited information in each pixel of CIFAR-10. Feature extraction is a key step in image classification, where during the analysis and handling of information in an image, the existing features remain unchanged, and these features are then extracted to solve the problem practically [4], [5]. However, the use of feature extraction has some drawbacks, including the fact that conventional feature extraction tends to be non-adaptive because the features are pre-programmed beforehand. Additionally, conventional layers only generate a limited number of features, which can restrict the model's ability to recognize complex objects or require more specific features for recognition [6]. Advanced techniques such as Principal Component Analysis (PCA) are necessary to overcome the limitations of conventional feature extraction. PCA is a feature extraction technique used to reduce the dimensionality of raw image inputs and the complexity of calculations involving multiple intercorrelated variables. This technique aimed to produce new, smaller, and independent variables [7], [8].

The application of PCA for image classification using Convolutional Neural Networks (CNN) is one of the most suitable algorithms to accommodate and implement a combination of both techniques [9]. CNN is a Deep Learning method that can be used for image classification. CNN has demonstrated its superior ability to achieve exceptional accuracy in the field of computer vision [10]. It can reduce the complexity of network structure and the number of parameters to be determined through local receptive fields, weight sharing, and pooling operations, thus achieving excellent results in image classification problems [11], [12], [13]. The popularity of CNN has significantly grown in various application domains related to computer vision, including object detection, segmentation, and localization, among others [14]. The application of CNN is highly beneficial in domains such as computer vision, as it greatly reduces the need for manual modeling processes due to its ability to learn from raw input data [15]. However, this model faces a gradient diffusion problem, which can cause slow updates to its underlying parameters during the training process [16]. According to [1], combining CNN with PCA has been proven to reduce iterations and optimization processes, simplify structure, and decrease training time compared to traditional CNN models while using an auto-encoder for the initial stage of model initialization.

The application of CNN and PCA resulted in faster data training compared to conventional feature extraction techniques. However, the combination of these two techniques has not shown a significant improvement in data accuracy, as demonstrated in several studies conducted by [17], [18], [19], these studies found that the combination of PCA and CNN did not yield optimal results, indicating the need for a new method, such as transfer learning. The application of the transfer learning method with the CNN model has been widely used to tackle various complex problems. The challenge in using this method lies in achieving high accuracy with relatively low computational cost. A literature study has explained that the implementation of transfer learning has proven to be superior compared to other methods. Research conducted by [20] demonstrates that the application of the transfer learning method on a large-sized COVID dataset achieved very good accuracy compared to models that did not apply transfer learning. Studies conducted by [21], [22] showed that the application of CNN and PCA yielded excellent results in the classification of medical images. Densely Connected Convolutional Networks (DenseNet) are often chosen for transfer learning due to their efficient feature reuse, reduced number of parameters, and improved gradient flow. These characteristics make DenseNet highly effective for fine-tuning pre-trained models on new tasks with limited data, leading to better performance and faster convergence [23].

Therefore, the application of PCA on CNN for image classification on the CIFAR-10 dataset using the transfer learning method will be investigated in this research to examine the effect of PCA in enhancing CNN performance with transfer learning. DenseNet was chosen for its efficient architecture, which retains features through densely connected layers and addresses the vanishing gradient issue.

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Each layer receives inputs from all previous layers, enhancing feature propagation, reducing parameters, and optimizing performance for small datasets [24]. Additionally, it works effectively with Principal Component Analysis (PCA) to understand and interpret the model's improved predictions, providing insight into feature extraction and data sufficiency [25]. Its design balances efficiency and accuracy, making it suitable for resource-constrained environments.

2. Materials and Methods

This research proposes a new combination of methods for image classification. The combination involves the use of PCA on CNN with DenseNet transfer learning. The first method is the implementation of PCA on CNN, where PCA reduces the dimensionality of raw images. The second method adds DenseNet transfer learning to the PCA and CNN framework. This research will use a pre-trained DenseNet model before applying PCA. Thus, this approach is expected not only to reduce the size of the image but also to provide additional benefits, such as reducing training time and improving the model's accuracy. The detailed process steps are shown in Fig 1.

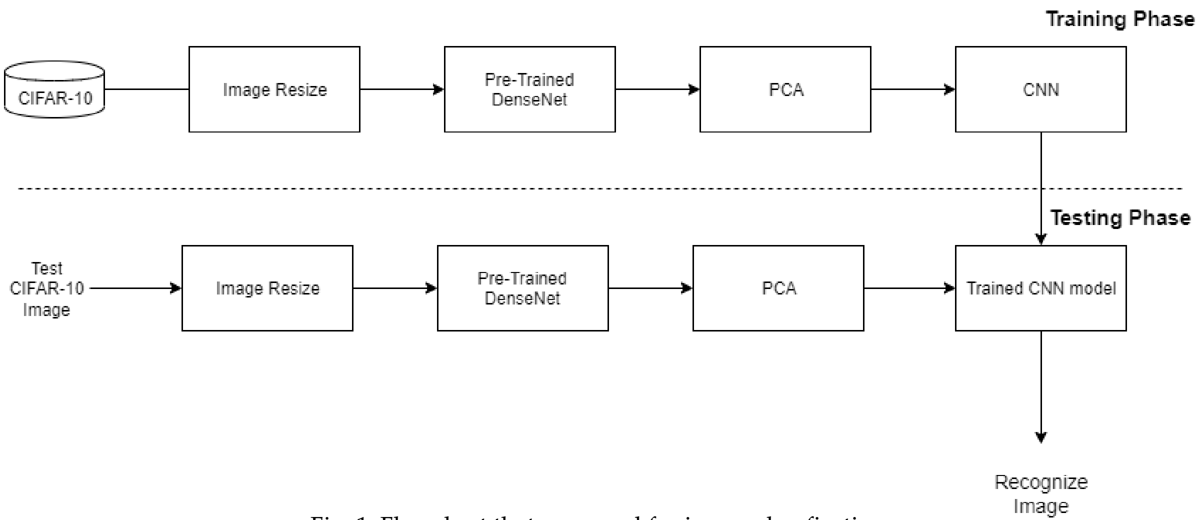

Fig. 1. Flowchart that proposed for image classfication

2.1 Previous Study

Several previous studies on image classification were conducted, such as in [26] which focused on classifying butterflies based on color and later converted to grayscale using KNN and GLCM. This successfully classified two classes out of a total of 4 butterfly classes with an error rate of 8.9%. CNN's ability to perform image classification is very broad. For instance, in [27], researchers used CNN to classify abnormalities in lung CT-scan images. They compared the accuracy of CNN with the region-based CNN feature (R-CNN), which means that in the R-CNN approach, researchers only used CNN for non-feature extraction approach. The results showed that both the CNN and R-CNN methods were satisfactory, achieving an average accuracy of 84.7% without the need for additional feature extractors to extract features from images.

Meanwhile, in the study conducted by [10] on image classification of CIFAR-10 and MNIST dataset, using PCA on CNN with an additional auto-encoder during the initialization phase achieved an accuracy of 98.92% and addressed the CNN gradient diffusion problem by applying PCA during the training process instead of on raw data. Additionally, the researchers found that a reduction in iteration time and the optimization of training time could be achieved with a simpler network structure and reduced hardware load.

In addition, a study conducted by [28] introduced the method of channel boosting in CNN and transfer learning. The problem faced by the researchers was that CNN had to handle high-dimensional and imbalanced data. To address this, the researchers explored the input layer stage using an auto-encoder to unravel the variance in the data. Furthermore, transfer learning was employed as a bridge in the output layer to create an additional layer, ensuring that all features could still be retained within the CNN, resulting in a new approach called Channel Boosted CNN (CB-CNN). This study achieved an AUC value of 0.81 and an accuracy of 84%.

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On the other hand, the use of PCA in CNN with transfer learning was explored by [29], who applied PCA to CNN with the help of a pre-trained model from AlexNet to detect hand gestures. The pre-trained AlexNet model was reduced in size using PCA. Then, the obtained features were retrained using CNN. The results showed an average accuracy of around 87.83%, compared to a regular CNN, which achieved a result of 73.86%. Meanwhile, research proposed by [30] employed a deep transfer learning method that combined VGG19 with PCA and Multi-Layer Perceptron (MLP) trained on a CNN architecture to achieve an average accuracy of 60% on the test data, with a total time required per epoch of 7.7 seconds. In comparison, DenseNet achieved a higher average accuracy score of 92.7% across multiple datasets, outperforming both ResNet and EfficientNet in terms of accuracy and convergence speed. DenseNet also efficiently balances accuracy with computational cost, making it particularly suitable for resource-constrained applications such as weather classification and small-scale data analysis.

2.2 Data Preparation

This study used the CIFAR-10 dataset, which consists of 60,000 images across 10 different classes, namely airplane, automobile, bird, cat, deer, dog, frog, horse, ship, and truck. The CIFAR-10 data was divided by default into training and testing sets with a proportion of 80:20, resulting in 50,000 images for training data and 10,000 for testing data. CIFAR-10 was collected and created by Alex Krizhevsky, Vinod Nair, and Geoffrey Hinton [2]. The dataset was then subjected to several treatments, including flattening, normalization, and resize.

The flattening process enables the PCA process to be performed at the input layer stage in CNN, where all the features are combined and transformed into a one-dimensional vector. The results of the flattening process are shown in Table 1.

Table 1. CIFAR-10 after flattening

Pixel 0	Pixel 1	Pixel 2	Pixel 3	⋯	Pixel 3069	Pixel 3070	Pixel 3071	Label
59	62	43	45	⋯	123	92	72	*Frog*
154	177	187	126	⋯	143	133	144	*Truck*
255	255	255	253	⋯	80	86	84	*Truck*
⋮	⋮	⋮	⋮	⋯	⋮	⋮	⋮	⋮
35	178	235	40	⋯	12	31	50	*Truck*
189	211	240	186	⋯	195	190	171	*Automobile*
229	229	239	236	⋯	163	163	161	*Automobile*

The data normalization was used to standardize the units of the CIFAR-10 image data. The normalization process scaled the value range of each pixel, for example, from 0 to 255 to 0 to 1. Data normalization was applied to both the training and test data of CIFAR-10. The purpose of normalization was to achieve a zero mean for the later PCA application and to avoid dominant variables that might affect the result. The detailed results of the normalization process are shown in Table 2.

Table 2. CIFAR-10 after normalization

Pixel 0	Pixel 1	Pixel 2	…	Pixel 3070	Pixel 3071	Label
0,231373	0,243137	0,247059	…	0,360784	0,282353	Frog
0,603922	0,694118	0,733333	…	0,521569	0,564706	Truck
1,0000000	1,0000000	1,0000000	…	0,337255	0,329412	Truck
⋮	⋮	⋮	…	⋮	⋮	⋮
0.137255	0.698039	0.921569	…	0.121569	0.196078	*Truck*
0.741176	0.827451	0.941176	…	0.745098	0.670588	*Automobile*
0.898039	0.898039	0.937255	…	0.639216	0.631373	*Automobile*

This step involved adjusting the image dimensions for transfer learning. By default, the CIFAR-10 dataset consists of 32x32 pixel images, which were resized to the minimum size required by denseNet, 224x224 pixels. This resizing process used synthetic data to fill in the missing pixels and achieve the desired size.

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2.3 Modelling

This research utilized several PCA models on CNN with transfer learning to classify CIFAR-10 data. For comparison, the researcher also employed PCA on CNN without transfer learning. The settings for each training process used the optimal configurations for CNN on CIFAR-10 data, as conducted by [31], with hidden layer configurations of 1024, 512, and 256 neurons, each using Relu activation function. The input layer was modified using PCA, and the output layer incorporated transfer learning. The input layer used in this study was transformed back from a one-dimensional vector into a three-dimensional vector.

2.3.1. Principal Component Analysis (PCA)

PCA was applied during the pre-processing and input layer stages. The application of PCA in the pre-processing stage resulted in eigenvalues, as shown in Table 3.

Table 3. Eigenvalue

	PCA 1	PCA 2	PCA 3
The largest eigenvalue	55.3633	21.4265	12.7469

This study utilized only the top 3 eigenvalues from the available eigenvalues, as these three eigenvalues already represent 88% of the variance in CIFAR-10. Then, PCA at the pre-processing stage was then applied to CIFAR-10, yielding the results as shown in Table 4.

Table 4. PCA on CIFAR-10

PCA 1	PCA 2	PCA 3	Label
-6.4010	2.7290	1.5017	Frog
0.8298	-0.9499	6.0038	Truck
7.7302	-11.5221	-2.7536	Truck

Table 4. shows the results of applying PCA to CIFAR-10, which significantly reduced the number of dimensions from the original 3072 pixels to 3 principal components used for training the CNN.

2.3.2. Convolutional Neural Network (CNN)

The CNN used in this study had a configuration consisting of 32 Conv2D, 2 Max pooling layers, 64 Conv2D, 2 Max Pooling, 128 Conv2D, and hidden layers with 1024, 512, and 256 neurons each, along with a Relu activation function. The details of the CNN architecture can be seen in Fig 2.

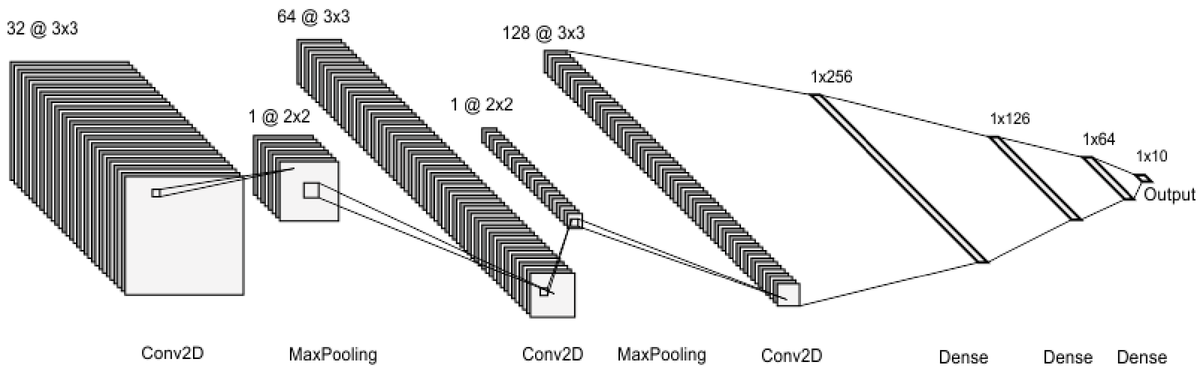

Fig 2. CNN architecture

2.3.3. PCA-CNN

In detail, the implementation of PCA in the training process of CNN was carried out by projecting the features generated by the convolutional layers into a lower-dimensional feature space using the PCA technique. PCA was applied to the feature matrix with the largest eigenvalues, thereby preserving the most informative features in the data. Next, the feature dimensions were reduced to approximately 50% of the original dimensions by selecting the principal components that contributed the most to the data variation. The PCA projection results were then processed by the subsequent layers in the CNN to train the model.

Dimensionality reduction using PCA can reduce the complexity of the model and the computational time required for model training. Additionally, this technique can eliminate correlations

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between features that may disrupt the training process and can improve model performance by reducing overfitting. However, before applying PCA to the training process in CNN, it is important to select the optimal number of principal components carefully. Excessive dimensionality reduction could lead to the loss of important information and negatively impact model performance. Therefore, the selection of the optimal number of principal components should be performed through experiments and testing on different training data.

2.3.4. PCA-CNN with transfer learning

During the training phase of CNN with transfer learning, the PCA technique could be optimized by leveraging a pre-trained base model. In this example, the transfer learning method used was DenseNet, one of the pre-trained base models on complex image datasets such as ImageNet. The DenseNet model can be used to extract high-quality features from images.

Next, to evaluate the effectiveness of applying PCA to the transfer learning training process, dog images from the Cifar-10 dataset were used as an example. In practice, applying PCA to features from the DenseNet model helps reduce the dimensionality of the data and improve model performance by removing correlations between irrelevant features. The transfer learning method using the DenseNet model can also enhance model performance by utilizing features that have been well-trained on large and complex image datasets, such as ImageNet. The combination of PCA and transfer learning with the DenseNet model on dog images from the Cifar-10 dataset provides significant benefits to the CNN model training process. Further details of the PCA architecture on CNN using transfer learning are shown in Fig 3.

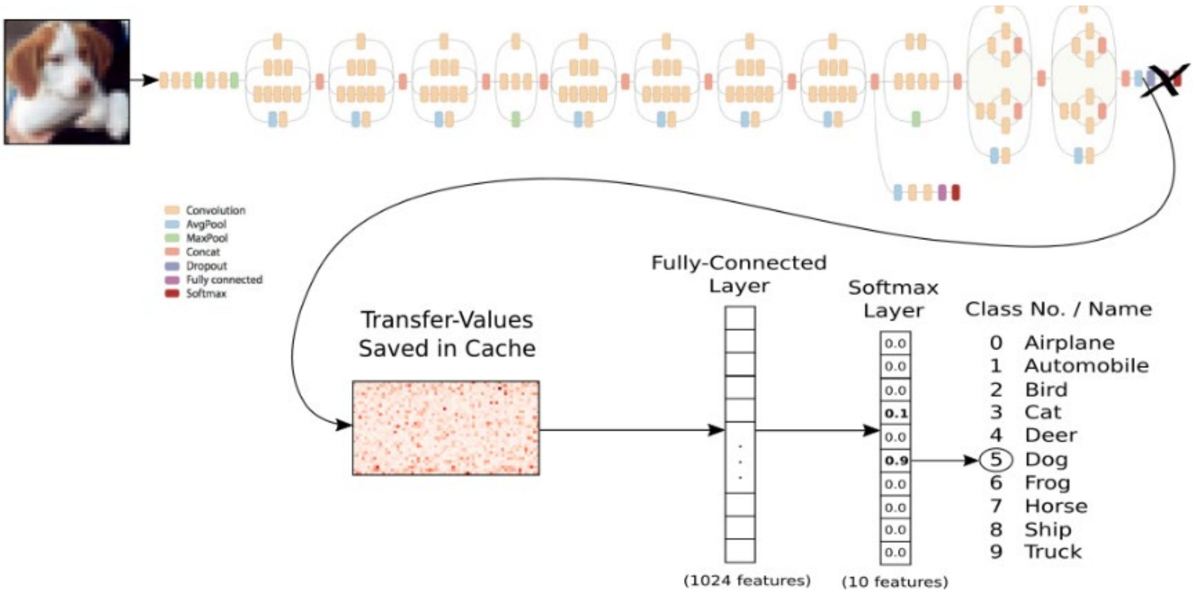

Fig 3. PCA on CNN with transfer learning

3. Results and Discussion

In this study, we conducted an analysis using the Transfer Learning method on Convolutional Neural Network (CNN) by applying the Principal Component Analysis (PCA) technique to improve image classification performance. The results of the experiments showed that the use of PCA method in transfer learning with CNN improved the image classification performance on the dataset used. Additionally, we analyzed the eigenvalues of PCA and found that high eigenvalues contribute significantly to the improvement of image classification performance. These results provide strong evidence that the use of PCA method in transfer learning with CNN can be an effective alternative for enhancing image classification performance.

3.1. PCA-CNN

In this experiment, we used the PCA-CNN method without transfer learning to improve image classification performance on the dataset. The results showed that using the PCA-CNN method without transfer learning can significantly improve image classification performance. At epoch 50, the accuracy reached 54.9%, but by epoch 200, the accuracy had decreased to 53.9%. However, we also observed that at epoch 150, the model experienced overfitting, where the classification performance on the training

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data was higher than on the validation data. This condition indicates that the model became too focused on the training data and was unable to generalize well to the validation data. These results demonstrate that the PCA-CNN method without transfer learning can be an effective alternative for image processing and improving classification performance, as shown in Table 5.

Table 5. The result of PCA on CNN

Epoch	Accuracy		Training Time
	Accuracy	Validation Accuracy	
50	0.9257	0.5491	2 minutes 22 seconds
100	0.9774	0.5506	5 minutes 23 seconds
150	**1.0000**	**0.7162**	6 minutes 17 seconds
200	0.9782	0.5394	8 minutes 32 seconds

Table 5 presents the results of the PCA on the CNN model obtained from 4 experiments with the same parameters. The best result was achieved at epoch 150, with an accuracy of 1.00 and a validation accuracy of 0.7162, with a total training time of 6 minutes and 17 seconds, or 2 seconds per epoch. However, the results indicate overfitting, as the model achieved 100% accuracy, suggesting that it only learned from the given data and cannot generalize well to new data.

3.2. PCA on CNN using transfer learning

In this experiment, we applied the PCA-CNN model with transfer learning to improve image classification performance on the CIFAR-10 dataset. The use of PCA-CNN with transfer learning on the CIFAR-10 dataset is expected to effectively and efficiently enhance image classification performance for each class. In the following sections, we will present the accuracy results of image classification for each experiment conducted using the PCA-CNN model with transfer learning on the CIFAR-10 dataset, and the results of this model are shown in Table 6.

Table 6. PCA on CNN with transfer learning

Epoch	Accuracy		Training Time
	Accuracy	Validation Accuracy	
50	0.7416	0.7568	55 minutes 28 seconds
100	0.8854	0.8692	1 hr 26 minutes 11 seconds
150	0.9108	0.8383	2 hrs 11 minutes 35 seconds
200	**0.9269**	**0.8982**	**4 hrs 5** minutes **12 seconds**

Table 6 presents the results obtained from the PCA-CNN model with transfer learning in 4 trials using the same parameters as those used in the PCA-CNN model, with four epochs tested. The best result was achieved at epoch 200, with an accuracy of 0.9269, a validation accuracy of 0.8982, and a total training time of 4 hours, 5 minutes, and 12 seconds, or 350 seconds per epoch.

3.3. Comparison

The process of using the PCA-CNN method involved utilizing a conventional CNN architecture without applying transfer learning. In contrast, for the PCA-CNN method with transfer learning, we used a pre-trained model from the DenseNet architecture on the CIFAR-10 dataset. The experimental results showed that the PCA-CNN method with transfer learning provided better image classification performance compared to the conventional PCA-CNN method in each epoch. In the following subsection, we will present the image classification accuracy results for each experiment conducted on both methods, as shown in Table 7.

Table 7. Comparison Result

Information	Method			
	PCA-CNN		PCA-CNN with Transfer Learning	
	Accuracy	Validation Accuracy	Accuracy	Validation Accuracy
Accuracy	1.0000	0.7162	0.9269	0.8982
Learning time	2 Seconds / Epoch		350 Seconds / Epoch	

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Table 7 shows that the PCA on CNN with the transfer learning method performed better than the conventional PCA on CNN method in classifying images on the CIFAR-10 dataset. This was because the PCA on CNN model with transfer learning did not exhibit signs of overfitting despite achieving higher accuracy on the training data compared to the PCA on CNN model, with scores of 100% and 92%, respectively. Additionally, the PCA on CNN with transfer learning demonstrated more stable accuracy and achieved higher accuracy on the test data.

As a comparison, a study conducted by [27] using the proposed hybrid transfer learning method with VGG19-PCA-MLP trained on a CNN architecture achieved an average accuracy 60% on the training data, with a total training time of 7.7 seconds per epoch. Meanwhile, the PCA on CNN model using DenseNet Transfer Learning achieved an accuracy of 71.62% on the test data, with a total training time of 2 seconds per epoch. In the study proposed by [26], a transfer learning approach using alexNet and PCA combined with linear regression on a CNN architecture, with a total of 10 classes for object detection and image data resolution reduced to 227x227x3, achieved an accuracy of 95%In contrats, this study's proposed PCA on CNN model using DenseNet transfer learning, with the initial data size increased to 227x227x3, achieved an accuracy of 89%.

The limitations of combining PCA, CNN, and DenseNet are multifaceted. Computational complexity arises due to DenseNet's dense connectivity and the pre-processing demands of PCA, which require significant computational resources and memory, particularly for high-dimensional and large datasets [32]. Furthermore, the combination poses risks of overfitting. While DenseNet's dense connections enhance feature reuse, they may struggle to generalize effectively when paired with PCA's tendency to oversimplify data. Implementing robust regularization strategies is essential to address these challenges and improve generalization across diverse datasets and applications [33].

4. Conclusion

The PCA model on CNN using transfer learning achieved better results than the PCA model on CNN alone. The accuracy comparison showed 55% for the PCA model on CNN and 88% for the PCA model on CNN with transfer learning. Additionally, factors such as the absence of overfitting, high accuracy, and precise classification highlight the superiority of the PCA model on CNN with transfer learning. These advancements have led to the development of the PCA-CNN-DenseNet model, which incorporates efficient feature reuse and reduced parameter requirements. This makes it suitable for key applications such as medical imaging. Integrating PCA with CNN-DenseNet reduces dimensionality and expedites training while retaining essential features, making it highly effective for diagnosing complex conditions such as lung abnormalities and brain tumors. Moreover, the PCA-CNN-DenseNet model supports real-time image analysis in applications such as autonomous vehicles, enabling reliable object detection and classification under diverse conditions. Furthermore, using transfer learning, PCA-CNN-DenseNet can be fine-tuned to identify plant disease symptoms with minimal data, supporting early detection and reducing crop losses in precision agriculture.

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