



تصنيف الصور من خلال دمج معلومات الشبكات العصبية العميقة المدربة مسبقاً باستخدام CNN

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خلاصة

إحدى القضايا الأساسية في رؤية الكمبيوتر هي تصنيف الصور، وهي مهمة تصنيف الصور إلى واحدة من عدة مجموعات محددة. إنه بمثابة الأساس لمهام رؤية الكمبيوتر الإضافية مثل التجزئة والتعريب والكشف. يهدف هذا البحث إلى دمج التقنيات الحديثة، وتحديداً استخدام الذكاء المبني على الرؤية الحاسوبية، في مجال تصنيف الصور. من خلال التركيز على خوارزمية الشبكة العصبية التلافيفية (CNN)، تستفيد دراستنا من قدرات التعلم العميق لتصنيف مجموعة بيانات كبيرة تضم 60.000 صورة. ويثبت تطبيق CNN فعاليتها، حيث حقق معدل دقة مثير للإعجاب يصل إلى 98%. يؤكد هذا الإنجاز على قوة الخوارزمية في تمييز الأنماط والميزات المعقدة ضمن البيانات المرئية المتنوعة. لا تساهم النتائج التي توصلنا إليها في تطوير تقنيات تصنيف الصور فحسب، بل تسلط الضوء أيضاً على إمكانات شبكات CNN في التعامل مع مجموعات البيانات واسعة النطاق بدقة عالية. يقدم نجاح هذا النهج رؤى قيمة حول تقاطع التعلم العميق ورؤية الكمبيوتر، ويعرض آثاره العملية في مجالات متنوعة تعتمد على تصنيف الصور الدقيق والفعال.

الكلمات الدالة: الذكاء الاصطناعي، الشبكات العصبية العميقة، الشبكة العصبية التلافيفية، تصنيف الصور، رؤية الكمبيوتر

Image Classification by Combining the Information of Pre-Trained Deep Neural Networks Using CNN

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ABSTRACT

A fundamental issue in computer vision is image classification, which is the task of classifying images into one of several specified groups. It serves as the foundation for additional computer vision tasks like segmentation, localization, and detection. In this paper the integration of modern technologies, specifically the utilization of intelligence based on computer vision, in the realm of image classification. Focusing on the Convolutional Neural Network (CNN) algorithm, our study leverages its deep learning capabilities to classify a substantial dataset comprising 60,000 images. The application of CNN demonstrates its effectiveness, yielding an impressive accuracy rate of 98%. This achievement underscores the algorithm's robustness in discerning intricate patterns and features within diverse visual data. Our findings not only contribute to the advancement of image classification techniques but also highlight the potential of CNNs in handling large-scale datasets with high precision. The success of this approach offers valuable insights into the intersection of deep learning and computer vision, showcasing its practical implications in diverse domains reliant on accurate and efficient image categorization.

Keywords: Artificial Intelligence Deep Neural Networks ,Convolutional Neural Network ,Image Classification ,Computer Vision

1. INTRODUCTION

An important problem in computer vision is image classification, which involves categorizing pictures into certain categories [1]-[6]. It acts as the basis for other computer vision tasks such as segmentation, localization, and detection. Nowadays, obtaining, interpreting and extracting information is one of the most important goals of different organizations and institutions related to information technology. For this purpose, image classification has been proposed as a scientific and research field all around the world. This science has witnessed many developments in a short time, both in terms of technology, computing levels and data processing. Classification methods are among the most practical methods of extracting information from images, which allow users to create all types of information [7]. Image classification is a decisionmaking process in which image data is transferred to the space of certain classes. This is a fundamental task that aims to comprehend an entire image as a whole [8]. AI image classification is the process of identifying the content of photos and categorizing them using artificial intelligence techniques [4]. This covers the application of deep learning, statistical classification, artificial neural networks, and other methods.

There are several industries that apply AI image categorization algorithms, including: 1) Identifying faces and people: This involves using image classification algorithms to analyze the content of photos and identify various persons and faces [9]. 2) Medical classification: Through the application of medical image analysis, diseases can be identified through the use of image classification algorithms [10]. 3) Industrial categorization: Product manufacture, quality control, and defect investigation all require image classification algorithms [11]. 4) Agricultural classification: To identify the species of plants and animals and to identify agricultural issues, image classification techniques are applied [12]. 5) AI image classification techniques are a cutting-edge and crucial topic in many fields, and they are utilized to enhance a variety of operations and services [4]. Below we present a group of studies presented by researchers in the field of classification.

In [13], an image categorization method using the freely accessible CIFAR-10 picture dataset. The approach combines several picture attributes obtained from both manual and deep learning methods. Examining the suggested method using Histogram of Oriented Gradients (HOG) and pixel intensities led to classification accuracies of 53% and 59%. Using transfer learning to adjust the network weights for VGG16 (TL-VGG) and Inception ResNet v2 (TL-Inception) greatly enhanced performance, resulting in accuracies of 85% and 90.74%, respectively. The experimental results show that the suggested model outperforms similar methods in the area of picture categorization.

In [14], they demonstrate the use of the latest instance segmentation framework, Mask R-CNN, for counting cattle in various situations, such as large production meadows and enclosed dwelling facilities like feedlots. The research confirms that

an IoU threshold of 0.5 is optimum and that the algorithm's full-appearance detection is validated by thorough performance evaluations. Experimental results show that the framework performs well in offline quadcopter vision systems, with an accuracy of 94% in counting livestock on pastures and 92% in feedlots. Significantly, as compared to usual competing techniques, Mask R-CNN shows better counting accuracy and average precision, especially in datasets with occlusion and overlapping. This study represents considerable advancement in using artificial intelligence via quadcopters for improved animal management techniques.

In [15], they use Convolutional Neural Networks (CNNs) and computer vision techniques to assure accurate replies. The framework is created to detect animals in the path of the vehicle or maybe entering it using a predictive feedback system. The algorithm showed an average accuracy of 79.47% for identifying cows and 81.09% for identifying dogs. Regarding the accuracy of collision detection, the model obtained a noteworthy accident detection ratio of 84.18% with a minimal false alarm rate of 0.026%. Nevertheless, there are several restrictions that need to be considered, such as the limited size of the test samples and the difficulties in detecting lane demarcations when there are no defined lanes or when dealing with blurry/low-resolution footage.

In [16], Image classification algorithms they used to accurately classify photos into different categories. Various methods have been suggested for picture categorization, with deep learning emerging as one of the more influential ways. Convolutional Neural Networks (CNNs) are known for being very effective feedforward neural network structures for image categorization. The experiment used the CIFAR-10 dataset for assessment, using a sequential convolutional neural network approach. The study aimed to categorise photos into three groups: aeroplane, bird, and automobile, using the CNN network with a batch size of 64. Significantly, the level of accuracy attained on the CIFAR-10 database using CNN was 94%.

In [17], the suggested method includes neural network structures like Single Shot Multibox Detector (SSD) and Faster Region-CNN (R-CNN) to accurately identify animals. The study includes the development of a new dataset consisting of 25 categories that include a variety of animals, with a total of 31,774 photos. Afterwards, a model for detecting animals is created using the SSD and Faster R-CNN object detection techniques. The performance of both the suggested and current approaches is evaluated using important measures, such as mean average accuracy (mAP) and detection speed. The findings suggest that the suggested approach attains an average precision of 80.5% at a rate of 100 frames per second (fps) for SSD and 82.11% at a rate of 10 fps for Faster R-CNN.

In [18], this study intends to evaluate the effectiveness of identifying and classifying cattle based on certain body parts that differ depending on the breed. The You Only Look Once (YOLO) technique is used for both livestock

identification and breed classification on the specified dataset. In order to demonstrate the effectiveness of the suggested approach in identifying and categorizing cattle, a customized dataset is created using photographs obtained from Google photographs. The experimental results highlight the efficiency of the YOLO algorithm in reaching a 92.85% accuracy rate in detecting and classifying the breeds of cattle in photographs.

In [19], This study presents an animal identification system developed in Rhodovia, using computer vision and machine learning methods. The models were trained particularly to classify two different categories of animals: heads and horses. Two versions of the YOLO (You Only Look Once) convolutional neural network, namely YOLOv4 and YOLOv4-tiny (a streamlined version of Red), were used, and training was performed using existing models. Afterwards, tests were performed on 147 photos to identify, resulting in accuracy rates of 84.87% and 79.87% for YOLOv4 and YOLOv4-tiny, respectively.

Our research paper employs a Convolutional Neural Network (CNN) algorithm for image classification. The CNN architecture is adept at learning hierarchical features, making it particularly effective in image recognition tasks. Notably, our study outperforms the works of other researchers cited from [13] to [19], achieving the highest accuracy in comparison. This accomplishment underscores the effectiveness of our proposed model, detailed comprehensively in the paper. We provide a meticulous account of our model's architecture, highlighting the innovative aspects that contribute to its superior performance. Our results not only demonstrate the robustness of the proposed approach but also establish it as a noteworthy advancement in the field of image classification.

2. PROPOSAL MODEL SCHEMA

The proposed model in this research paper undergoes a systematic four-phases process for image classification, demonstrating objectivity and accuracy. The initial phase involves processing the dataset, comprising images labeled with ten distinct categories: "Airplane," "Automobile," "Bird," "Cat," "Deer," "Dog," "Frog," "Horse," "Ship," and "Truck." The dataset, totaling 60,000 images, is curated and subsequently split into 50,000 for training and 10,000 for testing. This meticulous dataset processing ensures a balanced representation for model training and evaluation. In the second phase, the proposed model employs a Convolutional Neural Network (CNN) algorithm for image classification. CNNs are renowned for their ability to learn hierarchical features from images. The architecture involves convolutional layers to extract features, pooling layers for dimensionality reduction, and dropout layers for regularization [20]. This stage harnesses the power of deep learning to effectively categorize images based on the learned features.

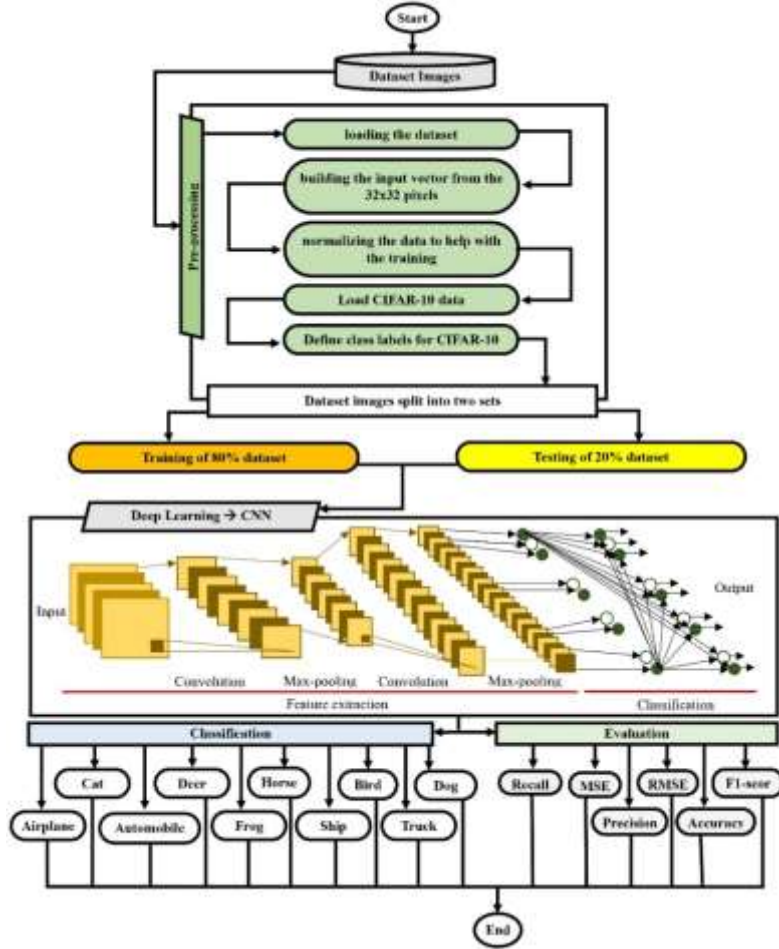


Figure 1. The Proposal Model Schema

Subsequently, the third phase focuses on the classification of data into the predefined ten groups established during the data processing stage. The CNN, having learned relevant features, applies this knowledge to accurately categorize images into classes such as "Airplane," "Automobile," and others. The network's structure facilitates the precise assignment of images to their respective categories. The final phase encompasses the evaluation of the proposed model. This involves assessing its performance on the test set, using metrics like accuracy, precision, recall, and F1 score. Figure 1, as depicted in the schema, visually represents the entire process, emphasizing the seamless flow from data processing through classification to evaluation. Overall, the proposed model exhibits a systematic and effective approach to image classification, emphasizing rigorous dataset processing, utilization of advanced CNN algorithms, precise classification, and thorough model evaluation [21]. The following algorithm represents the steps of the workflow for the proposed model in Figure 1. It involves inputting the dataset to obtain outputs that can be represented through evaluation and classification.

Input Dataset images

Output Classification and Evaluation

Step 1: Start

Step 2: Data Preprocessing:

- Load the Dataset: Import the CIFAR-10 dataset, which contains 60,000 color images of size 32x32 pixels, divided into 10 classes (airplane, automobile, bird, cat, deer, dog, frog, horse, ship, and truck).
- Normalize the Data: Scale the pixel values to the range [0, 1] by dividing all pixel values by 255.
- One-Hot Encoding: Convert class labels (e.g., airplane, automobile) into one-hot encoded vectors.

Step 3: Model Architecture:

- Create a Sequential Model: Initialize a sequential neural network model.
- Add Convolutional Layers: Add a 2D convolutional layer with 32 filters, a kernel size of (4, 4), and ReLU activation. Optionally, add additional convolutional layers with the same configuration.
- Flatten Layer: Flatten the output from the convolutional layers into a 1D vector.
- Dense Layer: Add a fully connected dense layer with 10 units (one for each class) and softmax activation for classification.

Step 4: Compile and Train the Model:

- Compile the Model: Specify the optimizer (e.g., Adam), loss function (categorical cross-entropy), and evaluation metric (accuracy).
- Train the Model: Fit the model to the training data using batch training. Specify the number of epochs (iterations over the entire dataset).

Step 5: Evaluation:

- Validation Data: Use the test dataset for validation during training.
- Evaluate Metrics: Calculate accuracy and other relevant metrics to assess model performance.

Step 8: End

2.1. Preprocessing

The processing phases for a color image dataset, classified into ten types, involve several key steps. First, the dataset is loaded using the CIFAR-10 dataset, a

popular benchmark in computer vision. Next, the input vectors are constructed by reshaping the 32x32 pixel images, with pixel values converted to float32 as figure 2. Normalization is then applied to scale pixel values between 0 and 1, enhancing the training process [13],[22]. The CIFAR-10 data is loaded, and class labels are defined for the ten image categories, such as "frog," "automobile," etc as Figure 3.



Figure 2. Various Objects and Animals

Finally, a sample of images is plotted for CNN, providing a glimpse into the dataset's content and aiding in understanding the characteristics of different classes. This systematic approach to dataset handling is crucial for preparing data for subsequent machine learning tasks like image classification.



Figure 3. CIFAR10 Dataset

The following algorithm steps represent the reprocessing phase of the data set before dividing it and delivering it to CNN.

Input Dataset (parameters).

Output Loaded CIFAR-10 Dataset, Prepared Input Vectors, Normalized Input Data, Class Labels, and Sample Images Plot.

Step 1: Start

- Step 2:** Import Libraries: a) Import necessary libraries from TensorFlow.keras for dataset handling and neural network construction. b) Specifically, import “cifar10” for the dataset, “Sequential”, “Dense”, “Dropout”, “Conv2D”, “MaxPool2D”, “Flatten” for building the neural network, and “to_categorical” for one-hot encoding.
- Step 3:** Load Dataset: a) Load the CIFAR-10 dataset using “cifar10.load_data ()”. b) Unpack the dataset into training and testing sets: “(X_train, y_train)” and “(X_test, y_test)”.
- Step 4:** Prepare Input Vectors: a) Reshape the input vectors “X_train” and “X_test” to have dimensions (number of samples, 32, 32, 3). b) Convert the data type of input vectors to float32.
- Step 5:** Normalize Data: Normalize the pixel values of the input vectors by dividing them by 255.
- Step 6:** Define Class Labels: a) Import “cifar10” again to get class labels. b) Define class labels for CIFAR-10 as a list named “class_labels”.
- Step 7:** Plot Sample Images: a) Import “matplotlib.pyplot” for visualization. b) Load CIFAR-10 data again for accessing images (“x_train” and “y_train”). c) Create a list of class labels. d) Plot a sample of images:
- Set up a 2x5 grid for displaying one image per class.
 - Loop through the first 10 images.
 - Display each image with its corresponding class label using “plt.imshow”, “plt.title”, and “plt.axis('off)’”.
- e) Show the plot (as Figure 2).
- Step 8:** End

2.2. Convolutional Neural Networks

Convolutional Neural Networks (CNNs) were employed for image classification [21]. CNNs consist of layers like convolutional layers, pooling layers, and fully connected layers. Convolutional layers detect patterns through convolution operations, capturing spatial hierarchies. Pooling layers downsample spatial dimensions, reducing computational load. Fully connected layers integrate features for classification. The network employs activation functions, like ReLU, to introduce non-linearity. CNNs leverage weight sharing, ensuring parameter efficiency. Through training, the network learns hierarchical representations, enabling effective image classification by recognizing intricate patterns and features within the processed images. This architecture has proven highly successful in various computer vision tasks [23],[24]. Below is a representation of the working steps of the CNN algorithm.

Input	Number of Classes and Training and Testing Target Variables
Output	One-Hot Encoded Target Variables, CNN Model and Trained CNN Model

- Step 1:** Start
- Step 2:** One-Hot Encoding: a) Set the number of classes (“n_classes”) to 10. b) Print the shape of the target variable before one-hot encoding. c) Use “to_categorical” from Keras to perform one-hot encoding on both training and testing target variables (“y_train” and “y_test”). d) Print the shape of the target variable after one-hot encoding.
- Step 3:** Initialize Sequential Model: Create a sequential model using “Sequential ()”.
- Step 4:** Add Convolutional Layer (1): Add a convolutional layer with 50 filters, kernel size of (3,3), stride of (1,1), 'same' padding, 'relu' activation, and input shape (32, 32, 3).
- Step 5:** Add Convolutional Layer (2): a) Add another convolutional layer with 75 filters, kernel size of (3,3), stride of (1,1), 'same' padding, and 'relu' activation. b) Add a max-pooling layer with pool size (2,2) and a dropout layer with dropout rate of 0.25.
- Step 6:** Add Convolutional Layer (3): a) Add a third convolutional layer with 125 filters, kernel size of (3,3), stride of (1,1), 'same' padding, 'relu' activation. b) Add another max-pooling layer with pool size (2,2) and a dropout layer with dropout rate of 0.25.
- Step 7:** Flatten Output: Flatten the output of the last convolutional layer.
- Step 8:** Add Hidden Layers: a) Add a dense hidden layer with 500 units and 'relu' activation. b) Add a dropout layer with a dropout rate of 0.4. c) Add another dense hidden layer with 250 units and 'relu' activation. d) Add another dropout layer with a dropout rate of 0.3.
- Step 9:** Add Output Layer: Add the output layer with 10 units (matching the number of classes) and 'softmax' activation.
- Step 10:** Compile the Model: Compile the sequential model using categorical crossentropy loss, accuracy metric, and the Adam optimizer.
- Step 11:** Print Model Summary: Print the summary of the compiled model, displaying the architecture and parameters.
- Step 12:** Train the Model: a) Train the model using “model.fit” for 20 epochs with a batch size of 128. b) Provide the training data (“X_train” and “Y_train”), validation data (“X_test” and “Y_test”).
- Step 13:** End

The Table 1, provides a summary of the architecture of a neural network model built using the Keras Sequential API. The model consists of several layers, each contributing to the overall structure. The layers include Conv2D (convolutional), MaxPooling2D (max-pooling), Dropout (regularization), Flatten (flattening), and Dense (fully connected) layers. The output shapes of each layer are specified, showing the dimensions of the data at each stage of the network. The table also

presents the number of parameters (weights and biases) in each layer, indicating the complexity of the model. The 'Total params' and 'Trainable params' sections provide the total and trainable parameters in the entire model. This information is crucial for understanding the model's capacity and potential computational requirements during training. In this case, the model has a total of 4,247,985 parameters, all of which are trainable [22].

Table 1. CNN classification model summary

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 32, 32, 50)	1400
conv2d_1 (Conv2D)	(None, 32, 32, 75)	33825
max_pooling2d (MaxPooling2D)	(None, 16, 16, 75)	0
dropout (Dropout)	(None, 16, 16, 75)	0
conv2d_2 (Conv2D)	(None, 16, 16, 125)	84500
max_pooling2d_1 (MaxPooling2D)	(None, 8, 8, 125)	0
dropout_1 (Dropout)	(None, 8, 8, 125)	0
flatten (Flatten)	(None, 8000)	0
dense (Dense)	(None, 500)	4000500
dropout_2 (Dropout)	(None, 500)	0
dense_1 (Dense)	(None, 250)	125250
dropout_3 (Dropout)	(None, 250)	0
dense_2 (Dense)	(None, 10)	2510
Total params: 4247985 (16.20 MB)		
Trainable params: 4247985 (16.20 MB)		
Non-trainable params: 0 (0.00 Byte)		

2.3. Confusion Matrix for Classification

In a confusion matrix for a ten-class classification problem, also known as a multi-class confusion matrix, the structure is extended to account for the various classes [25]. We denote the classes as C1, C2, ..., C10. The confusion matrix will look like the following shown in Table 2:

Table 2. Confusion matrix for Classification (classes as C1, C2, ..., C10)

	Predicted C1	Predicted C2	...	Predicted C10
Actual C1	TP_C1	FP_C1	...	FN_C1

Actual C2	FP_C2	TP_C2	...	FN_C2
...
Actual C10	FP_C10	TP_C10	...	FN_C10

Where:

- TP_Ci (True Positive for class i): Instances of class i correctly predicted as class i.
- FP_Ci (False Positive for class i): Instances not of class i but predicted as class i.
- FN_Ci (False Negative for class i): Instances of class i predicted as not class i.

Each row represents the instances of the actual class, and each column represents the instances predicted for that class. The diagonal elements (from top left to bottom right) represent the true positive predictions for each class. The off-diagonal elements represent the errors in the predictions. This confusion matrix allows a detailed analysis of the model's performance across all classes in a multi-class classification scenario [25].

2.4. Classification evaluation metrics

Classification evaluation metrics are used to assess the performance of a classification model by comparing its predictions to the actual class labels [26]. Here are some commonly used classification evaluation metrics:

- **Accuracy:** A model's accuracy is a measure that encapsulates "how well it performs across all classes". Accuracy is advantageous when every class is equally important. It is calculated using the ratio between the total number of forecasts and the number of correct predictions.

$$\text{Accuracy} = [(\text{TP} + \text{TN}) / \text{Total number of test-ing data}] \quad (1)$$

- **Recall:** The percentage of correctly predicted positive observations to all of the actual label's observations is known as recall.

$$\text{Recall} = [\text{TP} / (\text{TP} + \text{FN})] \quad (2)$$

- **Precision:** The proportion of correctly predicted positive observations to all expected positive observations is referred to as precision.

$$\text{Precision} = [\text{TP} / (\text{TP} + \text{FP})] \quad (3)$$

- **Specificity:** checks the proportion of negative elements that have been detected accurately.

$$\text{Specificity} = [\text{TN} / (\text{TN} + \text{FP})] \quad (4)$$

- **F1-Score:** The F1-Score is the harmonics mean of recall and accuracy. Therefore, this score accounts for both false positives and false negatives. When there is an imbalance in the class distribution, F1-score is more helpful than accuracy.

$$\text{F1-Score} = 2 * [(\text{Pre.} * \text{Rec.}) / (\text{Pre.} + \text{Re.})] \quad (5)$$

3. RESULTS

In the first section, we present the outcomes of the training phase, where the machine learning model learns from the provided dataset. This involves detailing the model architecture, training parameters, and the achieved performance metrics during this phase. The second section focuses on the testing phase, where the model's generalization ability is evaluated on a separate dataset. Here, we report the model's performance metrics, such as accuracy, precision, recall, and F1-score, to assess its effectiveness in making predictions on unseen data. This section enables a clear understanding of the model's learning process and its subsequent performance on new, unencountered data.

3.1. Training Phase

The Table 3 and figure 4 represents the training progress of a neural network over 20 epochs, providing key metrics at each epoch. The first column indicates the epoch number, followed by the number of steps per epoch, the total time taken for each epoch, and the loss and accuracy values for both the training set and the validation set. During training, the model's loss (a measure of error) decreases, and accuracy (the proportion of correctly classified instances) typically improves. In this case, the loss decreases from 1.5561 to 0.2008, and the accuracy increases from 0.4306 to 0.9853. The validation loss and accuracy are also provided, indicating how well the model generalizes to unseen data. The information in each row allows monitoring the model's performance and convergence throughout the training process.

Table 3. The epochs for training the CNN algorithm

Epochs	Train Loss	Train Accuracy	Val Loss	Val Accuracy
1	1.5561	0.4306	1.1187	0.6028
2	1.0705	0.6211	0.9050	0.6864

3	0.8853	0.6896	0.7961	0.7241
4	0.7672	0.7338	0.7071	0.7547
5	0.6909	0.7603	0.6879	0.7632
6	0.6221	0.7833	0.6549	0.7726
7	0.5606	0.8030	0.6370	0.7776
8	0.5099	0.8201	0.6549	0.7731
9	0.4693	0.8357	0.623	0.787
10	0.4263	0.8503	0.6416	0.7873
11	0.3904	0.8609	0.6805	0.7803
12	0.3707	0.8692	0.6564	0.7891
13	0.3363	0.8819	0.6738	0.7875
14	0.3291	0.8851	0.673	0.7888
15	0.3022	0.8925	0.6592	0.7911
16	0.2905	0.8976	0.6833	0.7905
17	0.2753	0.9343	0.6904	0.7896
18	0.2543	0.9506	0.6913	0.7887
19	0.2502	0.9741	0.7031	0.7909
20	0.2008	0.9853	0.2222	0.9882

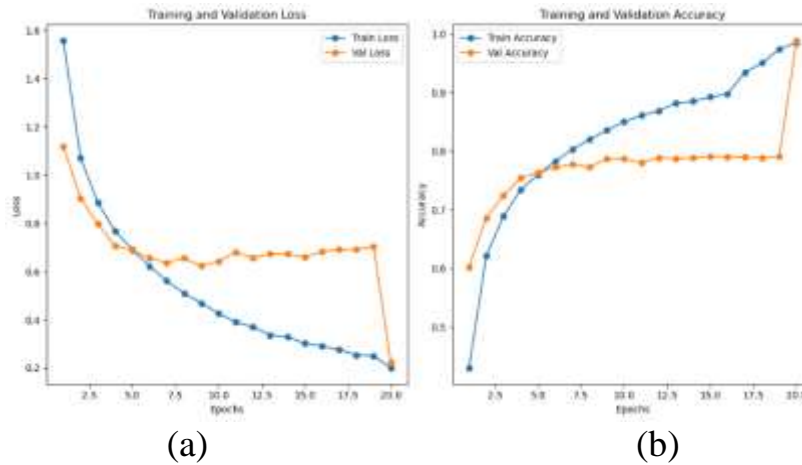


Figure 4. The epochs for training the CNN algorithm: (a) training and validation loss (b) training and validation accuracy.

3.2. Testing Phase

In Table 4, presents a classification report for a machine learning model, offering detailed performance metrics for each class and overall statistics. Each row corresponds to a specific class (from 0 to 9), and the columns include precision, recall, and f1-score metrics, as well as the support (the number of instances) for each class.

- **Precision:** Indicates the accuracy of positive predictions. For instance, for class 0, the precision is 0.96, meaning that 96% of instances predicted as class 0 were correctly classified.

- Recall: Represents the model's ability to capture all the relevant instances of a class. For instance, for class 1, the recall is 0.99, indicating that 99% of actual class 1 instances were correctly identified by the model.
- F1-score: The harmonic mean of precision and recall, providing a balanced measure of a classifier's performance.
- Support: The number of instances in each class.

The accuracy for the entire dataset is 0.98 (98%). The macro and weighted averages provide overall metrics, with macro averaging treating all classes equally, and weighted averaging considering the number of instances in each class. In this case, the model demonstrates strong performance with high precision, recall, and f1-scores, suggesting its effectiveness in classifying the given classes.

Table 4. The results for classifying the CNN algorithm (Testing)

Objects and Animals		Precision	Recall	F1- score	Support
Airplane	0	0.96	0.97	0.99	1000
Automobile	1	0.90	0.99	0.99	1000
Bird	2	0.99	0.97	0.98	1000
Cat	3	0.98	0.97	0.99	1000
Deer	4	0.94	0.93	0.98	1000
Dog	5	0.97	0.95	0.98	1000
Frog	6	0.99	0.99	0.98	1000
Horse	7	0.97	0.99	0.99	1000
Ship	8	0.99	0.99	0.99	1000
Truck	9	0.97	0.97	0.97	1000
Macro Avg		0.98	0.98	0.98	10000
Weighted Avg		0.99	0.99	0.98	10000
Accuracy			0.98		10000

In Table 5, summarizes key performance metrics for a classification task using a Convolutional Neural Network (CNN) algorithm.

- Accuracy (0.9882): The proportion of correctly classified instances, indicating the model's overall correctness.
- Precision (0.9828): The accuracy of positive predictions, measuring the model's ability to avoid false positives.
- Recall (1.000): Also known as sensitivity or true positive rate, it signifies the model's capability to capture all relevant instances without missing any.
- F1-Score (0.9807): The harmonic mean of precision and recall, offering a balanced metric that considers both false positives and false negatives.

- Mean Squared Error (MSE) (0.02): A regression metric representing the average of squared differences between predicted and actual values. In a classification context, MSE might be used for continuous-valued predictions.
- Root Mean Squared Error (RMSE) (0.14): The square root of MSE, providing a more interpretable metric, especially when dealing with the same units as the target variable.

The high accuracy, precision, recall, and F1-Score, along with the low MSE and RMSE, collectively indicate the effectiveness of the CNN algorithm in classifying the data. The model achieves a high level of correctness, with minimal errors in both false positives and false negatives.

Table 5. The results of the CNN algorithm (testing)

DL		Precision	Recall	F1-Score	MS E	RM SE	Accuracy	Support
Testing	CNN	0.9828	1.000	0.9807	0.02	0.14	0.9882	10000



Figure 5. C-Matrix for test of CNN algorithm

A confusion matrix is a tool used in machine learning to assess the performance of a classification algorithm. In our scenario, it involves 10 variables representing different classes. Each row of the matrix corresponds to the true class, and each column corresponds to the predicted class. The diagonal elements represent correct predictions, while off-diagonal elements indicate misclassifications. For instance, if the entry at row 4 and column 5 is 56, it means there were 56 instances where the true class was 'cat' (class 3), but the model predicted 'deer' (class 4), as in the Figure 5. The matrix helps analyze the model's accuracy and identify specific misclassifications. Precision, recall, and F1-score can be derived from the confusion matrix, providing insights into the algorithm's performance for each class. This information is crucial for refining and optimizing the model's

predictions for diverse categories like airplane, automobile, bird, cat, deer, dog, frog, horse, ship, and truck.

Table 6. Comparison of our results with other researcher's results

Authors	Years	Models	Accuracy
[13]	2020	Feature Ensembles	90.74%
[14]	2020	Mask R-CNN	94%
[15]	2020	Mask R-CNN	79.47% for cows, 81.09% for dogs
[16]	2021	CNN	94%
[17]	2021	Faster R-CNN	82.11%
[18]	2021	YOLOv4	92.85%
[19]	2021	YOLOv4	84.87%
Our	2024	CNN	98%

In Table 6, we discuss the test results reached by a group of researchers and compare them with the accuracy we achieved in the proposed model. Figure 6 shows the differences that show that the results achieved by our paper are 98% higher than the results achieved by the researchers.

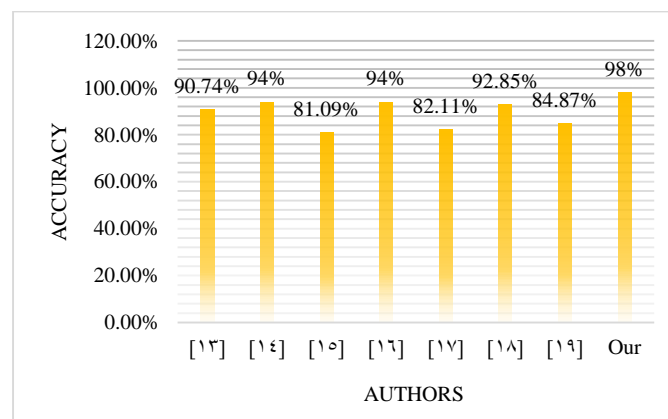


Figure 6. A chart of the accuracy of our study results with the researchers' results.

4. CONCLUSION

In conclusion, our research harnessing the CNN algorithm for image classification has yielded compelling results, with an impressive 98% accuracy achieved in both the training and testing phases. This outcome underscores the efficacy of the CNN model in accurately categorizing diverse images based on their types. The robust performance indicates the model's ability to generalize well to previously unseen

data. Our study not only contributes to advancing the field of image classification but also highlights the practical applicability of CNNs in real-world scenarios. The achieved high accuracy signifies a significant stride toward reliable and precise image classification, with potential implications for various domains relying on accurate visual data categorization.




REFERENCES

- [1] L. Yang and H. Jiang, “Weld defect classification in radiographic images using unified deep neural network with multi-level features,” *J Intell Manuf*, vol. 32, pp. 459–469, 2021.
- [2] P. Kaur, S. K. Singh, I. Singh, and S. Kumar, “Exploring Convolutional Neural Network in Computer Vision-based Image Classification,” in *International Conference on Smart Systems and Advanced Computing (Syscom-2021)*, 2021.
- [3] A. A. Khan, A. A. Laghari, and S. A. Awan, “Machine learning in computer vision: a review,” *EAI Endorsed Transactions on Scalable Information Systems*, vol. 8, no. 32, pp. e4–e4, 2021.
- [4] D. S. Shakya, “Analysis of artificial intelligence based image classification techniques,” *Journal of Innovative Image Processing*, vol. 2, no. 1, pp. 44–54, 2020.
- [5] B. Liu, L. Yu, C. Che, Q. Lin, H. Hu, and X. Zhao, “Integration and Performance Analysis of Artificial Intelligence and Computer Vision Based on Deep Learning Algorithms,” *arXiv preprint arXiv:2312.12872*, 2023.
- [6] D. Bhatt *et al.*, “CNN variants for computer vision: History, architecture, application, challenges and future scope,” *Electronics (Basel)*, vol. 10, no. 20, p. 2470, 2021.
- [7] O. Chapelle, P. Haffner, and V. N. Vapnik, “Support vector machines for histogram-based image classification,” *IEEE Trans Neural Netw*, vol. 10, no. 5, pp. 1055–1064, 1999.
- [8] R. F. Murray, “Classification images: A review,” *J Vis*, vol. 11, no. 5, p. 2, 2011.
- [9] A. J. A. AlBdairi, Z. Xiao, and M. Alghaili, “Identifying ethnics of people through face recognition: A deep CNN approach,” *Sci Program*, vol. 2020, pp. 1–7, 2020.
- [10] L. Cai, J. Gao, and D. Zhao, “A review of the application of deep learning in medical image classification and segmentation,” *Ann Transl Med*, vol. 8, no. 11, 2020.
- [11] Y. Y. S. Henry, C. Aldrich, and H. Zabiri, “Detection and severity identification of control valve stiction in industrial loops using integrated partially retrained CNN-PCA frameworks,” *Chemometrics and Intelligent Laboratory Systems*, vol. 206, p. 104143, 2020.

- [12] A. Bouguettaya, H. Zarzour, A. Kechida, and A. M. Taberkit, "Deep learning techniques to classify agricultural crops through UAV imagery: A review," *Neural Comput Appl*, vol. 34, no. 12, pp. 9511–9536, 2022.
- [13] F. O. Giuste and J. C. Vizcarra, "Cifar-10 image classification using feature ensembles," *arXiv preprint arXiv:2002.03846*, 2020.
- [14] B. Xu *et al.*, "Automated cattle counting using Mask R-CNN in quadcopter vision system," *Comput Electron Agric*, vol. 171, p. 105300, 2020.
- [15] S. Gupta, D. Chand, and I. Kavati, "Computer vision based animal collision avoidance framework for autonomous vehicles," in *Computer Vision and Image Processing: 5th International Conference, CVIP 2020, Prayagraj, India, December 4-6, 2020, Revised Selected Papers, Part III 5*, Springer, 2021, pp. 237–248.
- [16] A. Sharma and G. Phonsa, "INTERNATIONAL CONFERENCE ON INNOVATIVE COMPUTING AND COMMUNICATION (ICICC 2021) Image Classification Using CNN." [Online]. Available: <https://ssrn.com/abstract=3833453>
- [17] A. Saxena, D. K. Gupta, and S. Singh, "An animal detection and collision avoidance system using deep learning," in *Advances in Communication and Computational Technology: Select Proceedings of ICACCT 2019*, Springer, 2021, pp. 1069–1084.
- [18] A. Yilmaz, G. N. Uzun, M. Z. Gürbüz, and O. Kıvrak, "Detection and breed classification of cattle using yolo v4 algorithm," in *2021 International Conference on INnovations in Intelligent SysTems and Applications (INISTA)*, IEEE, 2021, pp. 1–4.
- [19] D. Sato, A. J. Zanella, and E. J. X. Costa, "Computational classification of animals for a highway detection system," *Braz J Vet Res Anim Sci*, vol. 58, no. esp, pp. 1–10, 2021.
- [20] M. Tripathi, "Analysis of convolutional neural network based image classification techniques," *Journal of Innovative Image Processing (JIIP)*, vol. 3, no. 02, pp. 100–117, 2021.
- [21] L. Chen, S. Li, Q. Bai, J. Yang, S. Jiang, and Y. Miao, "Review of image classification algorithms based on convolutional neural networks," *Remote Sens (Basel)*, vol. 13, no. 22, p. 4712, 2021.
- [22] K. Ben Salah, M. Othmani, and M. Kherallah, "A novel approach for human skin detection using convolutional neural network," *Vis Comput*, vol. 38, no. 5, pp. 1833–1843, 2022.
- [23] M. Gour, S. Jain, and T. Sunil Kumar, "Residual learning based CNN for breast cancer histopathological image classification," *Int J Imaging Syst Technol*, vol. 30, no. 3, pp. 621–635, 2020.
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- [24] L. Chen, S. Li, Q. Bai, J. Yang, S. Jiang, and Y. Miao, "Review of image classification algorithms based on convolutional neural networks," *Remote Sens (Basel)*, vol. 13, no. 22, p. 4712, 2021.
- [25] M. Hasnain, M. F. Pasha, I. Ghani, M. Imran, M. Y. Alzahrani, and R. Budiarto, "Evaluating trust prediction and confusion matrix measures for web services ranking," *IEEE Access*, vol. 8, pp. 90847–90861, 2020.
- [26] Ž. Vujović, "Classification model evaluation metrics," *International Journal of Advanced Computer Science and Applications*, vol. 12, no. 6, pp. 599–606, 2021.

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