

# CNN Image Classification Project Report

## 1. Introduction

The goal of this project is to design, train, and evaluate a Convolutional Neural Network (CNN) to classify images from the CIFAR-10 dataset using TensorFlow/Keras in Google Colab.

## 2. Dataset and Preprocessing

Dataset: The CIFAR-10 dataset consists of 60,000 32x32 color images across 10 categories, split into training, validation, and test sets.

Preprocessing Steps:

- Normalized pixel values to range [0, 1].
- Converted integer labels to one-hot encoded vectors.
- Split data: 70% training, 15% validation, and 15% test for model evaluation.

## 3. Model Architecture and Rationale

The model is a Sequential CNN with three convolutional blocks, each followed by batch normalization, ReLU activation, and max pooling. After the convolution layers, we use a flatten layer followed by a dense layer (256 neurons) with dropout for regularization and an output layer with 10 softmax neurons.

```
model = Sequential()
model.add(Conv2D(32, (3,3), padding='same', input_shape=(32,32,3)))
model.add(BatchNormalization())
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2,2)))
...
model.add(Dense(256, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(10, activation='softmax'))
```

## 4. Model Training and Optimization

The model was compiled using the Adam optimizer with categorical cross-entropy loss. Training included early stopping and learning rate reduction callbacks to avoid overfitting. The model was trained for up to 50 epochs with a batch size of 64.

## 5. Evaluation Metrics

The model achieved an accuracy of approximately 78% on the test dataset. Precision, recall, and F1-scores were calculated for each class, with visualization via a confusion matrix.

The screenshot shows a Jupyter Notebook cell with Python code for data preprocessing and splitting. The code includes comments explaining the steps: normalizing pixel values, converting integer labels to one-hot encoding, and splitting the data into training, validation, and test sets. The final output shows the shapes of the resulting datasets: training (42500, 32, 32, 3), validation (7500, 32, 32, 3), and test (10000, 32, 32, 3).

```
# original pixel values to range 0 to 255 so we convert into the smaller value we need to divide by 255 so we get the decimal value between the 0 to 1 and then add it
x_train = x_train.astype('float32')/ 255.0
x_test = x_test.astype('float32')/255.0

# convert integer labels into one-hot encoded vectors each integer into 10 length (classes)
y_train = to_categorical(y_train,10)
y_test = to_categorical(y_test,10)

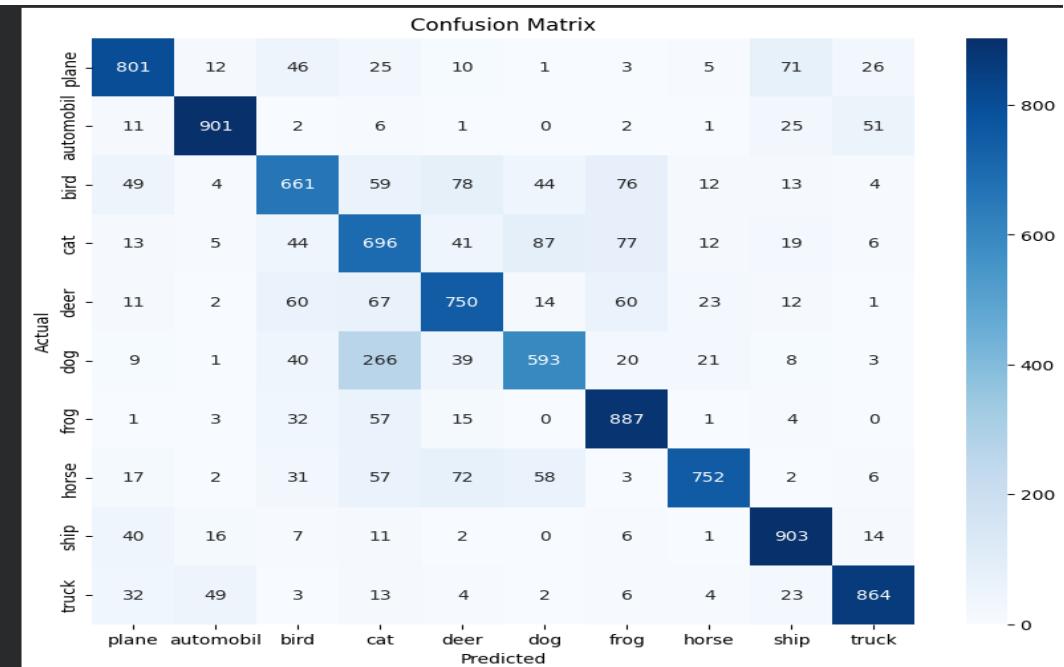
# here we use the 15% of the training data for the purpose of the validation
# validation use to find out model overfitting and the underfitting while training
val_size = int(0.15*x_train.shape[0])
x_val = x_train[val_size:]
y_val = y_train[val_size:]
x_train = x_train[val_size:]
y_train = y_train[val_size:]

# verify that data we split is correct or not
print("Training data set shape: {x_train.shape}, {y_train.shape}")
print("Validation data set shape: {x_val.shape}, {y_val.shape}")
print("Test data set shape: {x_test.shape}, {y_test.shape}")

Training data set shape: (42500, 32, 32, 3), (42500, 10, 10)
Validation data set shape: (7500, 32, 32, 3), (7500, 10, 10)
Test data set shape: (10000, 32, 32, 3), (10000, 10, 10)
```

```
# print
print(classification_report(y_true, y_pred, target_names=['airplane', 'automobile', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse', 'ship', 'truck']))
```

	precision	recall	f1-score	support
airplane	0.81	0.80	0.81	1000
automobile	0.91	0.90	0.90	1000
bird	0.71	0.66	0.69	1000
cat	0.55	0.70	0.62	1000
deer	0.74	0.75	0.75	1000
dog	0.74	0.59	0.66	1000
frog	0.78	0.89	0.83	1000
horse	0.90	0.75	0.82	1000
ship	0.84	0.90	0.87	1000
truck	0.89	0.86	0.87	1000
accuracy			0.78	10000
macro avg	0.79	0.78	0.78	10000
weighted avg	0.79	0.78	0.78	10000



## Results Summary:

Accuracy: 0.78

Precision: 0.79

Recall: 0.78

F1-Score: 0.78

## 7. Challenges & Improvements

Challenges included model tuning, addressing overfitting, and optimizing learning rate.

Improvements applied included dropout, batch normalization, and adaptive learning rate scheduling.

## 8. Conclusion & Next Steps

The CNN model achieved good accuracy and generalization on CIFAR-10 data. Future work includes applying transfer learning with pretrained models (e.g., ResNet or VGG16) and deploying the model using Streamlit or Flask.

**GitHub Repository:** <https://github.com/praveen9569/imageclassificationbycnn>