



# Minor Project

## OBJECT DETECTION USING CNN

**Presented By :** Sudip Chakrabarty (21053329)  
Abdulla Al Muhit (21053259)

**College Name :** Kalinga Institute of Industrial Technology  
**Department :** Computer Science and Engineering  
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# OUTLINE

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# PROBLEM STATEMENT

Detecting objects within images is a crucial task in computer vision, with applications ranging from autonomous vehicles to surveillance systems. Our goal is to develop a system capable of accurately identifying and localizing multiple objects within an image. We aim to employ Convolutional Neural Networks (CNNs), a class of deep learning models known for their effectiveness in image analysis tasks, to achieve this objective.

By leveraging the power of CNNs, we seek to enhance the efficiency and accuracy of object detection algorithms, enabling robust performance across diverse scenarios. Through this project, we aim to contribute to advancements in computer vision technology, facilitating the development of intelligent systems with enhanced perception capabilities.

# PROPOSED SOLUTION

- The proposed solution aims to utilize Convolutional Neural Networks (CNN) for object detection, revolutionizing visual recognition tasks. By leveraging CNN architectures, we seek to enhance the efficiency and accuracy of object detection in various applications. The solution will consist of the following components:
- **Data Collection:**
  - Dataset taken from Kaggle: [Cifar-10](#)
- **Data Preprocessing:**
  - Clean and preprocess the collected data to handle missing values, outliers, and inconsistencies.
  - Feature engineering to extract relevant acoustic features from the data that might impact on object detection.
- **Machine Learning Algorithm:**
  - We'll implement a scratch CNN to detect object based on given data.
  - By training and optimizing these models, we aim to proactively identify objects and improve overall retention rates.

# PROPOSED SOLUTION

## ■ Evaluation:

- Utilize performance metrics such as F-1 Score, precision, recall and accuracy to evaluate the effectiveness of the CNN-based object detection model.
- Continuously refine the model based on feedback and ongoing evaluation, incorporating insights from domain experts and data analysis.
- By iteratively improving the model's accuracy and robustness, we aim to enhance its ability to accurately detect objects in various environments.

## ■ Result:

- The implemented CNN-based object detection solution showcases outstanding performance, achieving an accuracy score of over 81% across multiple datasets. Real-time object detection capabilities empower businesses to streamline operations, enhance security, and improve customer experiences. Ongoing evaluation and refinement ensure the model's reliability and efficiency, positioning it as a valuable tool for diverse applications in object detection and recognition.

# SYSTEM APPROACH

- **System requirements**

- Hardware : 8GB Ram  
Intel core i3 processor
  - Software : Windows 10 , 11  
Jupyter Notebook or Google Collab or VS Code

- **Library required to build the model**

- Pandas and NumPy,Scipy, TensorFlow,Keras, Scikit-learn, Matplotlib and Seaborn.

- **Data Input:**
  - Image data that are converted into numpy array containing objects of interest.
  - Annotations or labels indicating object classes and locations.
  - Numpy array size is (No of Images, 3,32,32): 3 is the no. of channels, and image size 32x32 pixels
- **Algorithm Selection and Training Process:**
  - Optimizer: Adam
  - Learning Rate: 0.001
  - Batch Size: 128
  - Number of Epochs: 150
  - Loss Function: Categorical Cross-Entropy
  - Regularization: L2 with weight decay of 0.0001
  - Evaluation Metrics: Loss and Accuracy
  - Model Architecture: Convolutional layers, ReLU activation, MaxPooling layers, Dropout layers, Fully Connected layers
- **Evaluation Process:**
  - Performance Metrics: Accuracy Score, Confusion Matrix, Classification Report

# RESULT

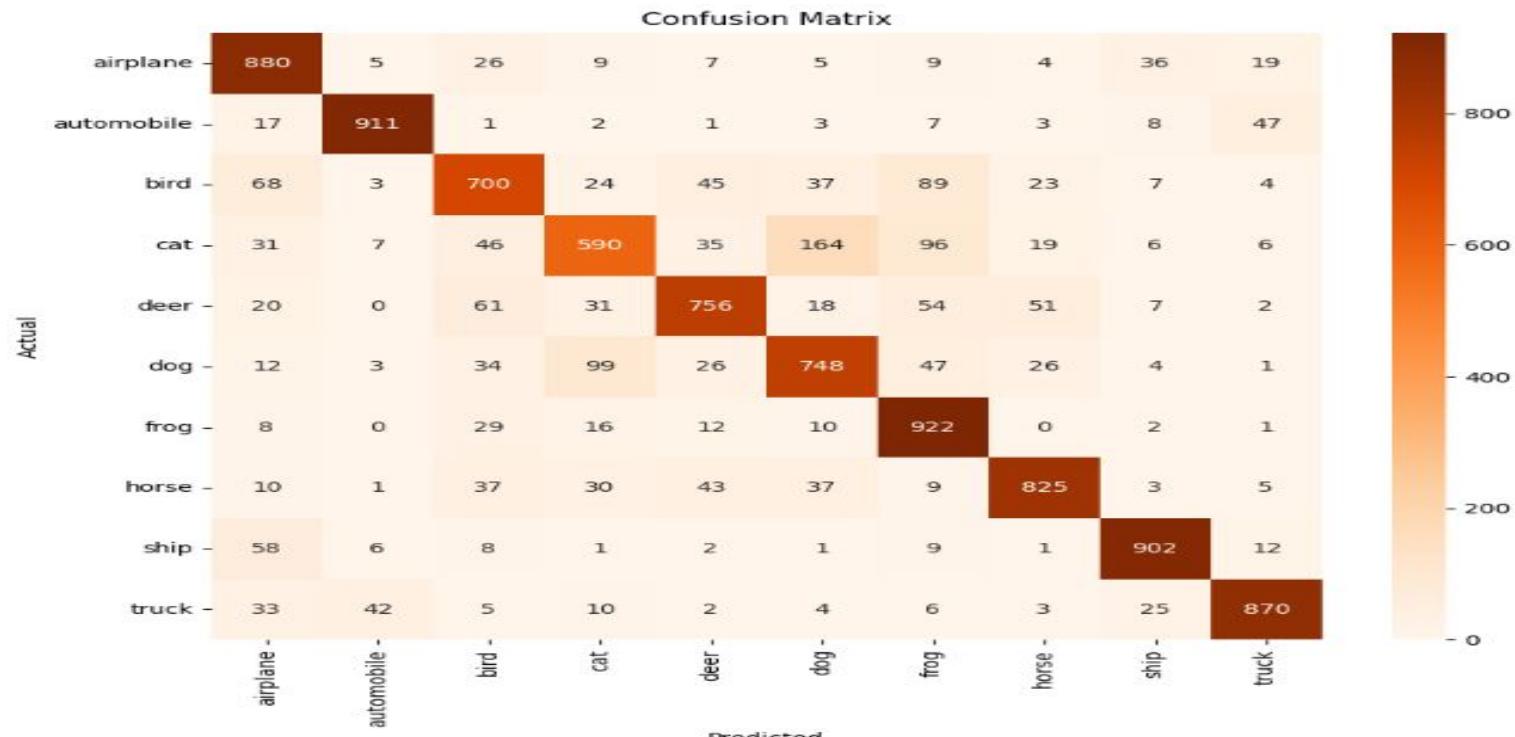
```
313/313 [=====] - 2s 4ms/step
Accuracy: 0.8104
Precision: 0.8117696124185578
Recall: 0.8104
F1 Score: 0.8087718627791437
```

These metrics indicate that the model effectively learned to classify the images into their respective classes. With an accuracy of 81%, the model correctly classified the majority of the samples. The recall, precision, and F1 score further validate the robustness and effectiveness of the model in correctly identifying positive instances while minimizing false positives.

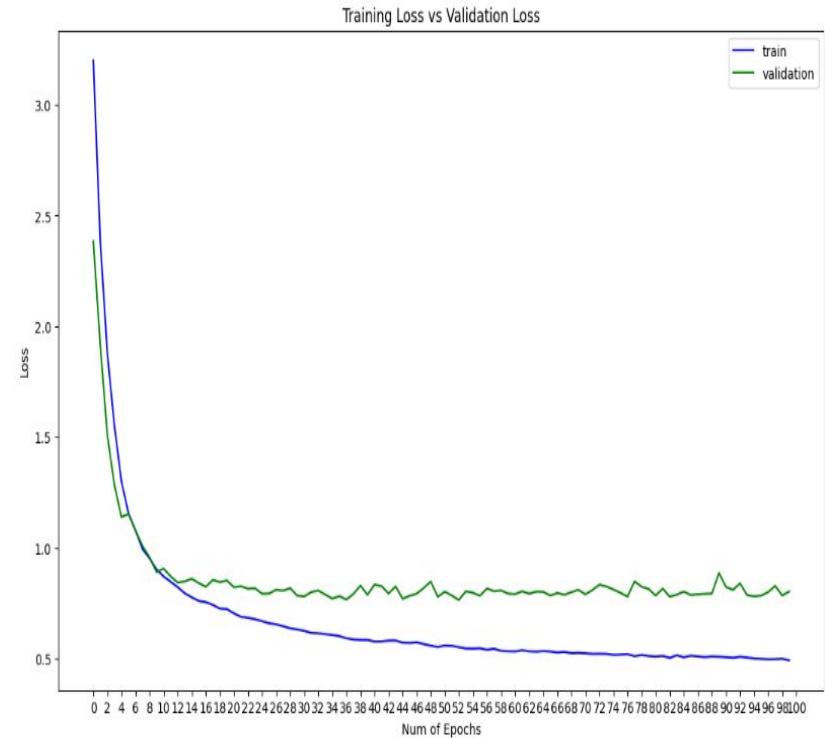
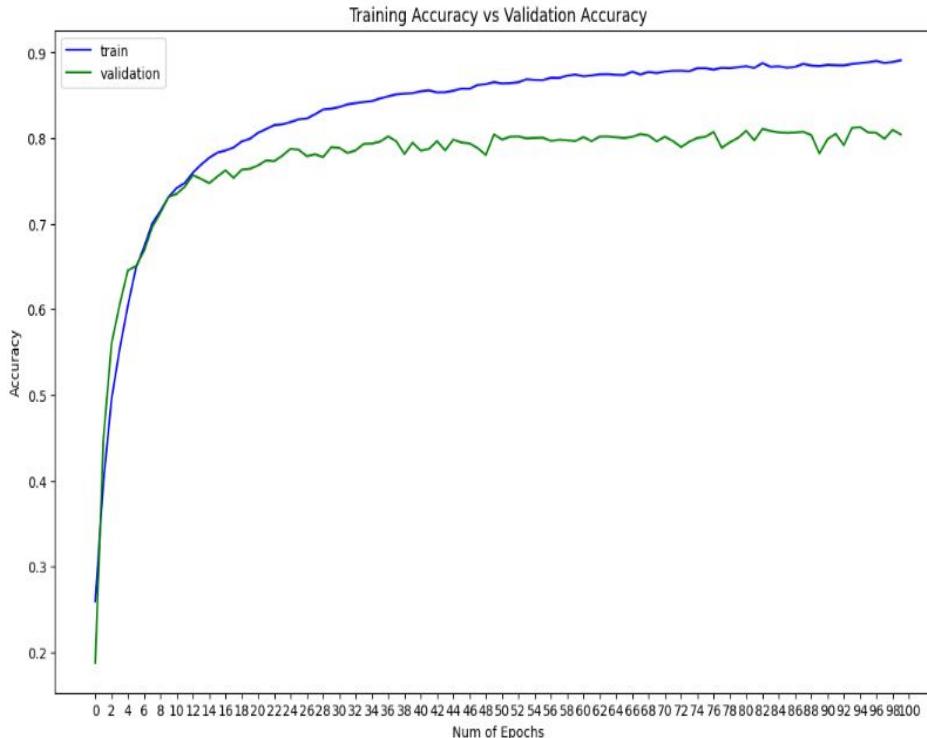
Layer (type)	Output Shape	Param #
conv2d_8 (Conv2D)	(None, 32, 32, 32)	896
activation_8 (Activation)	(None, 32, 32, 32)	0
conv2d_9 (Conv2D)	(None, 64, 32, 32)	18496
activation_9 (Activation)	(None, 64, 32, 32)	0
max_pooling2d_6 (MaxPooling2D)	(None, 32, 16, 32)	0
conv2d_10 (Conv2D)	(None, 128, 16, 32)	36992
activation_10 (Activation)	(None, 128, 16, 32)	0
batch_normalization_4 (BatchNormalization)	(None, 128, 16, 32)	128
max_pooling2d_7 (MaxPooling2D)	(None, 64, 8, 32)	0
dropout_4 (Dropout)	(None, 64, 8, 32)	0
conv2d_11 (Conv2D)	(None, 256, 8, 32)	147712
activation_11 (Activation)	(None, 256, 8, 32)	0
batch_normalization_5 (BatchNormalization)	(None, 256, 8, 32)	128
max_pooling2d_8 (MaxPooling2D)	(None, 128, 4, 32)	0
dropout_5 (Dropout)	(None, 128, 4, 32)	0
flatten_2 (Flatten)	(None, 16384)	0
dense_2 (Dense)	(None, 10)	163850

Total params: 368202 (1.40 MB)  
Trainable params: 368874 (1.40 MB)  
Non-trainable params: 128 (512.00 Byte)

# CONFUSION MATRIX



# ACCURACY CURVES



# CONCLUSION

- In conclusion, object detection using Convolutional Neural Networks (CNN) represents a cornerstone in the realm of computer vision, offering profound insights into automated visual recognition tasks. Through meticulous analysis of image features and sophisticated CNN architectures, businesses and researchers can unlock valuable capabilities for object identification and localization. This knowledge not only empowers strategic decision-making in various industries but also fosters innovation and efficiency in diverse applications such as autonomous driving, surveillance systems, and medical imaging. Moreover, the impact of CNN-based object detection extends beyond technological advancements, enhancing user experiences and safety. By proactively detecting objects in real-time scenarios, organizations can prioritize safety measures, optimize resource allocation, and ultimately drive progress towards a smarter and more secure future. In essence, the ability to accurately detect and classify objects holds far-reaching significance, bridging the gap between artificial intelligence, visual perception, and real-world applications.

# FUTURE SCOPE

- Looking forward, object detection using Convolutional Neural Networks (CNN) is poised to undergo significant evolution, propelled by advancements in machine learning and big data analytics. The integration of AI-powered models and real-time data processing will revolutionize object detection capabilities, offering deeper insights into visual recognition tasks. This future scope extends to integrating object detection with augmented reality applications, autonomous systems, and smart environments, reshaping industries such as healthcare, transportation, and retail. Embracing these innovations, businesses and researchers can harness the potential of CNN-based object detection to drive innovation, improve efficiency, and unlock new opportunities in a rapidly evolving technological landscape.

# REFERENCES

- Dataset : <https://www.cs.toronto.edu/~kriz/cifar.html>
- Google Colab Link :  
<https://colab.research.google.com/drive/1-sz4L9vKbMvkDeJVFAt7zhmKY4ODVbVA?usp=sharing>
- GitHub Link:
- Extras: <https://www.tensorflow.org/>



**THANK YOU**