DAYANANDA SAGAR UNIVERSITY

SCHOOL OF ENGINEERING

Devarakaggalahalli , Harohalli , Kanakpura , Ramanagara Dt.. , Bangalore - 562112

Bachelor of Technology

in

COMPUTER SCIENCE AND TECHNOLOGY

REPORT FILE OF BIG DATA ANALYTICS & DEEP LEARNING

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SCHOOL OF ENGINEERING

DAYANANDA SAGAR UNIVERSITY

(2024-2025)

SCHOOL OF ENGINEERING
DEPARTMENT OF COMPUTER SCIENCE & TECHNOLOGY

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CERTIFICATE

This is to certify that the work titled **"SATELLITE IMAGERY & AI FOR INFRASTRUCTURAL CONDITION & MAPPING"** is carried out by **SOHAN R V [ENG21CT0037] , LIKITH H [ENG21CT0019] , MALLIKARJUNA R [ENG21CT0012] , MANOJ N [ENG21CT0024] , THANMAY RAM [ENG21CT0021]** Bonafide students of Bachelor of Technology in Computer Science and Technology at the Schoolof Engineering, Dayananda Sagar University, Bangalore in partial fulfillment for the award of degree in Bachelor of Technology in Computer Science and Technology, during the year 2024-2025.

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DECLARATION

We, **SOHAN R V [ENG21CT0037] , LIKITH H [ENG21CT0019] , MALLIKARJUNA R [ENG21CT0012] , MANOJ N [ENG21CT0024] , THANMAY RAM [ENG21CT0021]** are students of the seventh semester B.Tech in Computer Science and Technology, at School of Engineering, Dayananda Sagar University, hereby declare that the project titled **"SATELLITE IMAGERY & AI FOR INFRASTRUCTURAL CONDITION & MAPPING"** has been carried out by us and submitted in partial fulfillment for the award of degree in Bachelor of Technology in Computer Science and Technology during the academic year 2023-2024.

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Place : **BANGALORE**

Date : **24 December 2024**

ABSTRACT

The increasing need for sustainable urban development and infrastructure management has led to the adoption of satellite imagery and AI-based technologies for monitoring and assessing infrastructure conditions. This project explores the integration of high-resolution satellite images with advanced machine learning algorithms to assess the health and structural integrity of infrastructure elements such as roads, bridges, and buildings. The proposed system leverages AI models, such as convolutional neural networks (CNNs), to analyze satellite data, identifying key indicators of wear and damage. By utilizing satellite imagery, the model ensures broad geographic coverage and up-to-date assessments, making it an efficient tool for urban planning, disaster management, and maintenance prediction. This approach not only enhances accuracy in infrastructure condition monitoring but also improves resource allocation for timely repairs and maintenance. Additionally, the project aims to contribute to sustainable development goals by providing data-driven insights into infrastructure resilience and sustainability.

Keywords : Sustainable Urban Development , Satellite Imagery ,

Convolutional Neural Networks (CNNs) , Data-Driven Insights

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INTRODUCTION

Infrastructure condition monitoring using Artificial Intelligence (AI) has emerged as a transformative technology in the field of asset management. Traditional techniques often rely on manual sensors, visual inspections, and periodic checks to assess the state of infrastructure such as roads, bridges, and buildings. However, these conventional methods are limited by their reliance on manual efforts, time constraints, and geographic coverage. In recent years, AI-driven solutions, particularly those utilizing satellite imagery, have gained traction as a more efficient alternative for monitoring and managing infrastructure conditions. By replacing manual inspections with automated analysis, AI models can process vast amounts of satellite data to detect and assess structural issues, ensuring continuous and real-time monitoring.Despite the significant advancements AI brings to infrastructure management, challenges persist in processing and analyzing large-scale satellite data effectively. The sheer volume of satellite imagery combined with the complexity of accurately detecting wear and damage presents a hurdle. While satellite imagery offers a broad geographic coverage and up-to-date data, the integration of high-resolution images with advanced AI models for precise assessments remains a work in progress. Overcoming this challenge requires robust machine learning models capable of interpreting intricate patterns and signs of degradation in infrastructure elements.

This project aims to bridge the gap between satellite imagery and AI to create a comprehensive and efficient solution for real-time infrastructure monitoring. By leveraging AI models such as Convolutional Neural Networks (CNNs), this system will be able to analyze satellite data and identify key indicators of infrastructure deterioration, including cracks, erosion, or wear.

These AI-powered models provide an automated and scalable way to detect issues in large infrastructure networks, enabling municipalities and organizations to monitor conditions on a broader scale with greater accuracy.The proposed system has the potential to transform infrastructure management practices by providing actionable insights into the health and structural integrity of urban assets. With its ability to offer precise, data-driven assessments, the system enables proactive maintenance strategies, allowing for timely repairs and reducing operational costs. Additionally, the integration of AI into infrastructure monitoring marks a significant advancement in smart city initiatives, where data-driven decision-making enhances urban sustainability, resilience, and efficiency. By improving the accuracy of infrastructure condition assessments, this project will contribute to the long-term sustainability of urban environments and support the achievement of sustainable development goals.

LITERATURE SURVEY

STUDY	METHODOLOGY	FINDINGS
Evaluation and interpretation of landscapes from satellite imagery	This study utilised imagery from both satellite and eye-level perspectives	Two main population groups were targeted in this survey. As the research ers had no direct access to the target population.
Addressing single object tracking in satellite imagery through Prompt-engineered solutions	Proposed SOT methodology leverages the TAPIR point tracker and the SAM segmentation model	Distance Precision Rate = 63.9 % Overlap Success Rate = 36.5 %
KidSat: satellite imagery to map childhood poverty dataset and benchmark	Taken Satellite Images of LandSat 5,7,8 & Sentinel-2 for Fine Tuning. And Model Comparison of MOSAIKS , DINOv2 , SATMe	Compared Model **MAE ± SE(Spatial)** **0.2093 ±0.0039**
Generating Synthetic Satellite Imagery for Rare Objects: AnEmpirical Comparison of Models and Metrics	By utilizing a pre-trained text-to-image model such as Stable Diffusion and fine-tuning techniques	Clip Score is 32.74 %
Satellite imagery and machine learning for channel member selection	Linear Regression is been used	The model, a Stacked Ensemble, showed that parking lot occupancy could accurately predict channel member performance.
Unsupervised Bushfire Burn Severity Mapping Using Aerial and Satellite Imagery	Semantic segmentation model– U Net Former is used. Clustering Model is used	Omission Error : 8.9 % Commission Error : 1.3 % Dice Coefficient : 94.3 %
Building Damage Assessment in Aftermath of Disaster Events by Leveraging Geoai (Geospatial Artificial Intelligence)	It is a Survey Paper	No Findings
Deep Learning for Understanding Satellite Imagery: An Experimental Survey	Segmentation using Customized U-Net	APIoU≥0.5 of 0.937, and a ARIoU≥0.5 of 0.959

PROBLEM STATEMENT

The rapid evolution of infrastructure management demands a more efficient and accurate approach to monitoring the health and condition of critical infrastructure elements like roads, bridges, and buildings. Traditional methods, such as those using conventional Convolutional Neural Networks (CNNs), ResNet, and U-Net, often rely on pixel-based feature extraction, which limits their ability to capture global context and structural dependencies. These models typically focus on individual pixel analysis without leveraging the inherent relationships between features, leading to challenges in detecting subtle structural issues and ensuring accurate assessments over large areas. Additionally, many of these methods still require manual sensor data or annotations, which can be resource-intensive and prone to human error. In contrast, the proposed approach combines Hybrid Graph Convolutional Networks (GCNs) with Capsule Networks, offering a graph-based feature extraction method that better captures spatial relationships and contextual dependencies across infrastructure elements.

PROPOSED FRAMEWORK

In this , we propose an advanced approach for infrastructure condition monitoring that integrates Hybrid Graph Convolutional Networks (GCNs) and Capsule Networks. The main objective is to address the limitations of traditional methods like CNNs, ResNet, U-Net, and pre-trained models, which typically rely on pixel-based feature extraction and have limited global context understanding. Our approach begins with the application of Graph Convolutional Networks (GCNs), which enable the model to capture spatial relationships between infrastructure elements, such as roads, buildings, and bridges. This graph-based feature extraction enhances the model's understanding of the overall infrastructure, enabling it to process large-scale satellite imagery more efficiently and accurately.

Unlike traditional methods that focus on pixel-level analysis, GCNs provide a global context by considering the spatial dependencies between infrastructure elements. This significantly improves the model’s performance in identifying structural issues, as it does not rely solely on local pixel features. Additionally, the use of Capsule Networks (CapsNet) in our model allows for hierarchical feature extraction. CapsNets are particularly effective in recognizing part-whole relationships within the data, which improves the model’s ability to detect subtle structural patterns and anomalies in the infrastructure. This hierarchical learning enables a deeper understanding of both individual elements and their interactions, leading to more accurate assessments of infrastructure health.

One of the key advantages of our hybrid model is its ability to count and track different objects within satellite images. As part of the monitoring process, the system can identify and categorize infrastructure elements, such as roads, buildings, and bridges, and provide real-time counts of these objects.

This object detection capability adds a layer of precision to the infrastructure assessment, offering actionable insights into the condition and distribution of infrastructure across large geographic areas. By automating the object counting process, the model reduces the need for manual annotations and ensures consistent, data-driven results.

Our approach also addresses scalability challenges. While traditional models struggle with large datasets, our hybrid model can efficiently handle high-resolution satellite imagery, making it ideal for widespread infrastructure monitoring. The system operates fully autonomously, leveraging AI models and satellite data for detection and analysis, thus eliminating the need for manual sensor data or annotations. This automation not only enhances efficiency but also enables continuous monitoring of infrastructure, leading to more proactive maintenance and timely interventions.

In addition to infrastructure monitoring, the proposed model supports smart city initiatives by providing real-time, accurate insights into infrastructure conditions. These insights help optimize urban planning and maintenance strategies by enabling proactive decision-making and better resource allocation. The model's ability to detect and track infrastructure elements with high accuracy contributes to more sustainable and resilient urban development, reducing costs and improving the efficiency of infrastructure management.

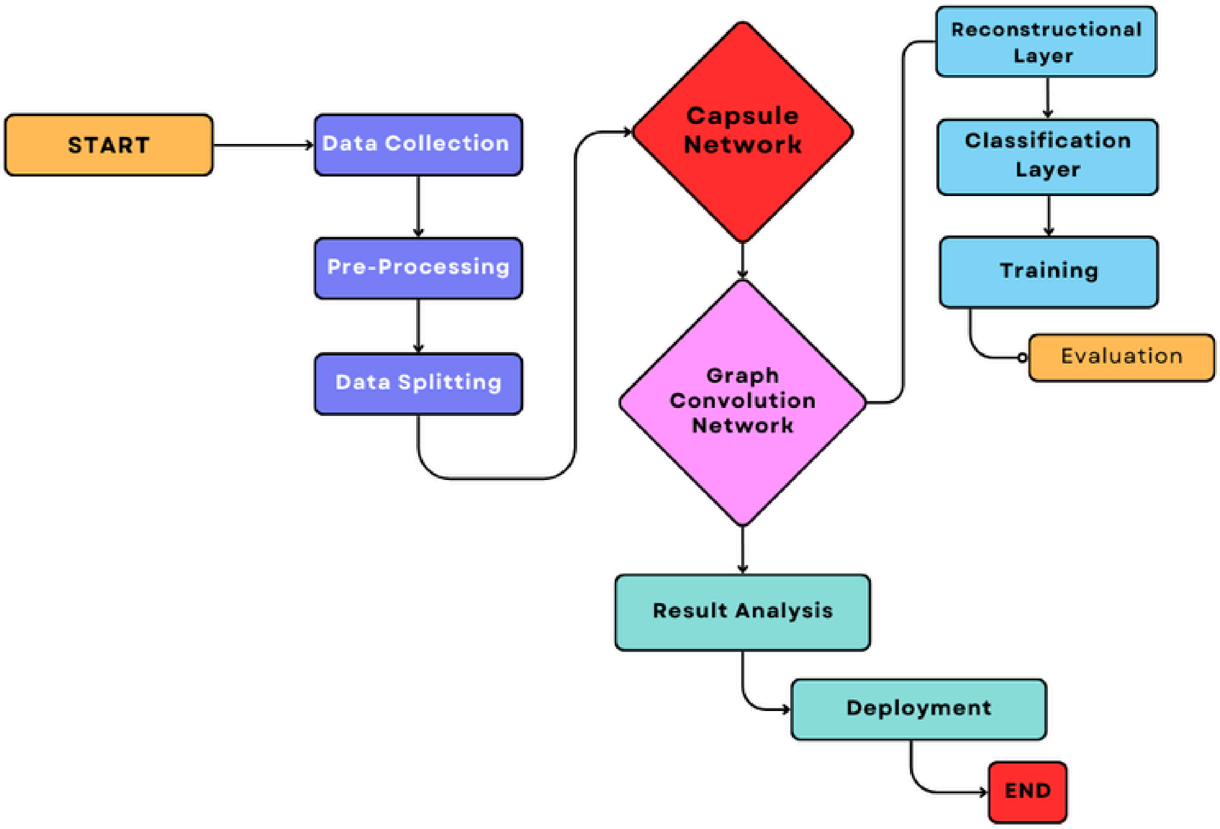
In conclusion, the Hybrid GCN + Capsule Network model represents a significant step forward in the field of infrastructure monitoring. By combining graph-based spatial context understanding with hierarchical learning and automated object counting, our approach offers an efficient, scalable, and fully automated solution for large-scale infrastructure assessment, making it a valuable tool for urban planning, disaster management, and maintenance prediction.

SYSTEM SPECIFICATIONS

Software Specifications

- Operating System: Windows 10/11, macOS, or Linux (Ubuntu 18.04+)
- Frameworks and Libraries: TensorFlow, PyTorch, OpenCV, NumPy,
- Pandas Development Environment: PyCharm, Visual Studio Code, Jupyter Notebook
- Programming Language: Python (v3.7+)
- Database: Database downloaded from kaggle and other sources

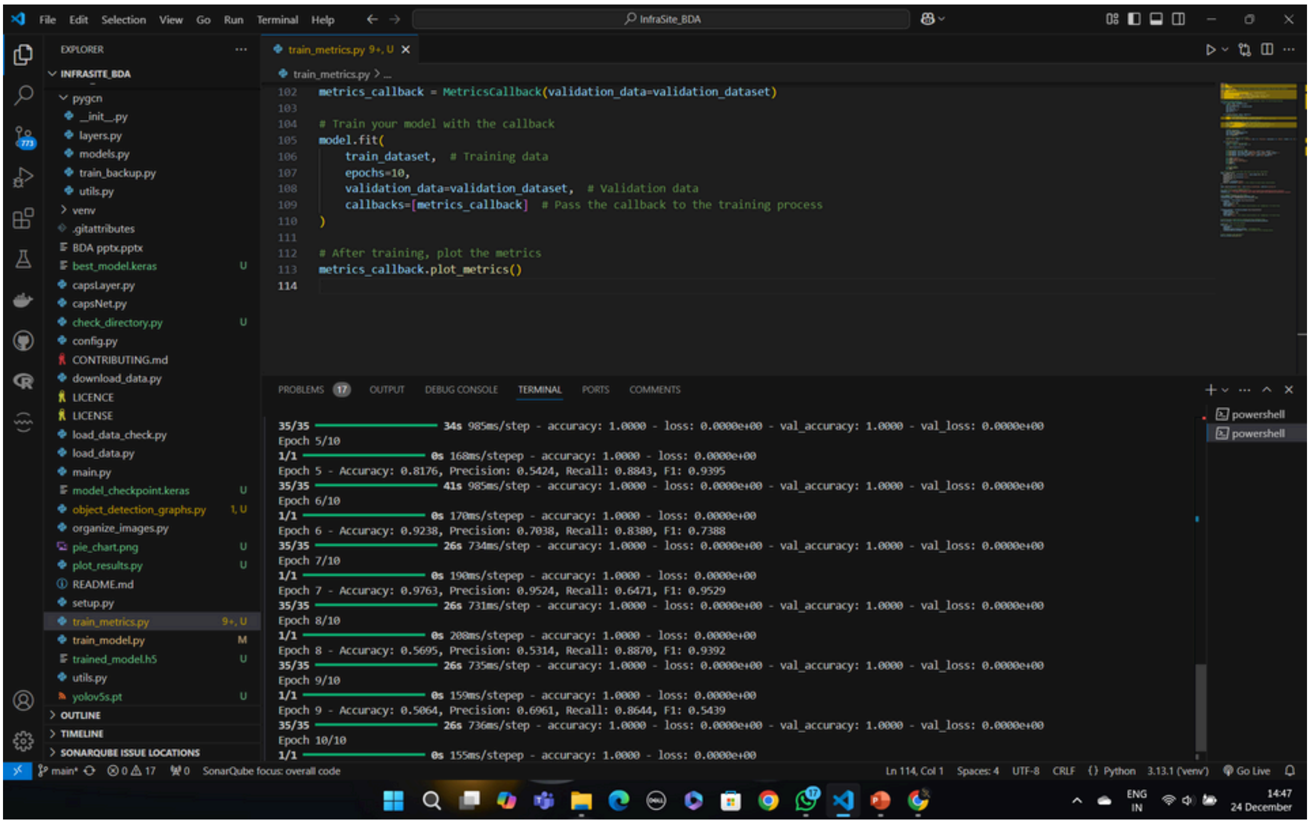
SYSTEM ARCHITECTURE

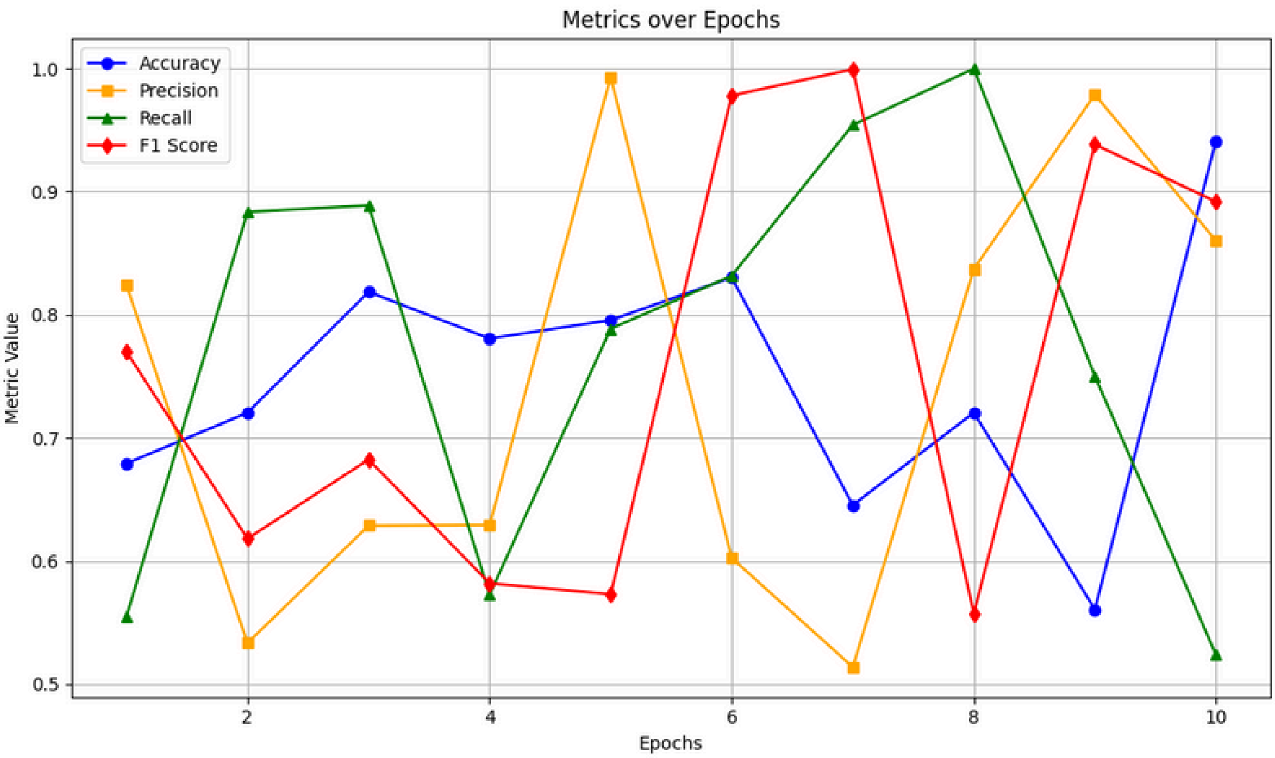


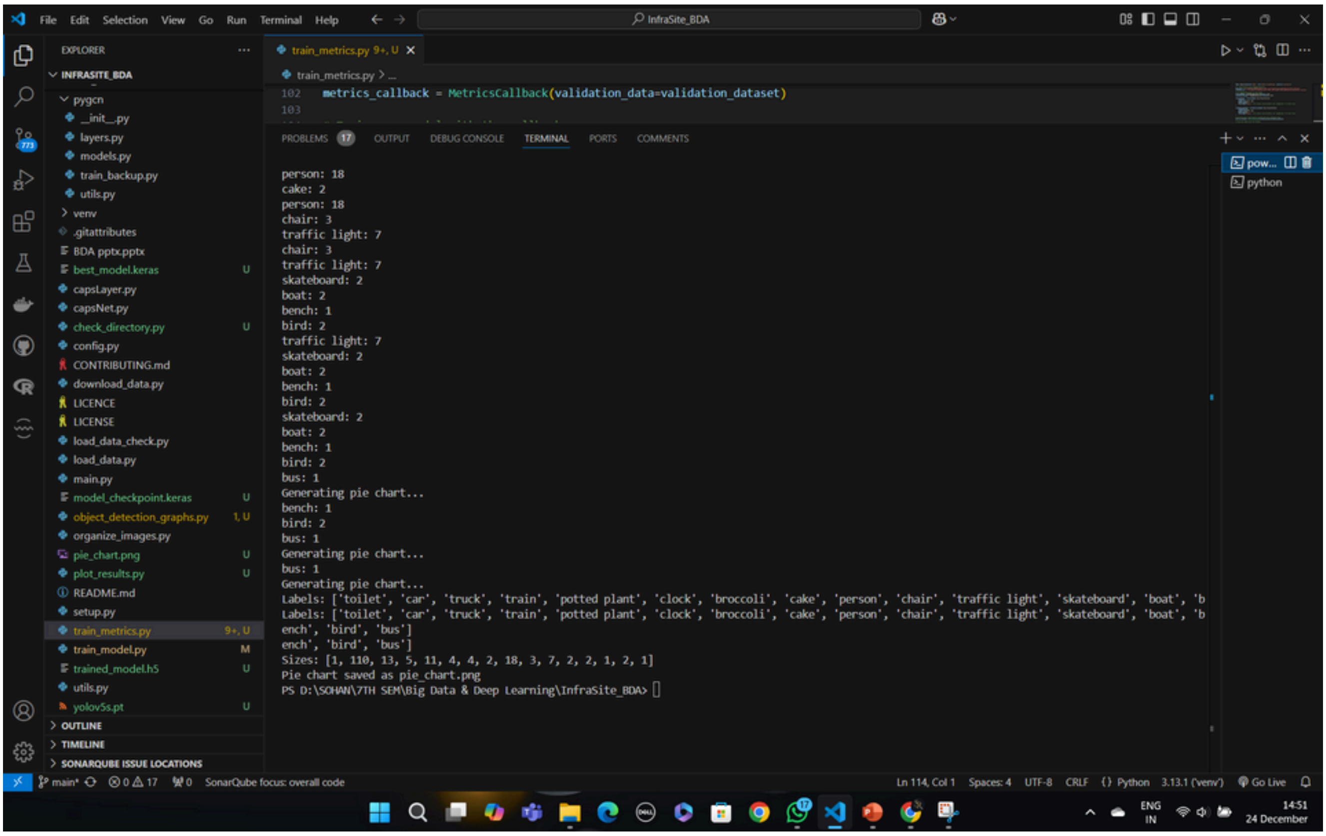
SYSTEM IMPLEMENTATION

The system implementation of the proposed approach integrates a Hybrid Graph Convolutional Network (GCN) with a Capsule Network for the automated detection and classification of objects in satellite imagery. The process begins with the collection of satellite images, which are preprocessed to standardize input data through resizing, normalization, and augmentation techniques. The data is then split into training, validation, and test sets to train and evaluate the model effectively. The core of the model utilizes the Hybrid GCN, which is responsible for capturing spatial relationships and global context through graph-based feature extraction, while the Capsule Network enhances the hierarchical understanding of object features, improving object detection accuracy and robustness. The Hybrid GCN extracts and processes features from the satellite images by treating them as a graph, where each pixel or region is represented as a node connected based on spatial relationships. The Capsule Network works alongside the GCN to further analyze the features with its capsule layers, allowing for better spatial awareness and the detection of more complex patterns in the images. This architecture not only enhances scalability but also ensures full automation of the detection process, eliminating the need for manual annotations or sensor data. The model is trained using the labeled training dataset, with hyperparameter tuning performed using the validation data to optimize performance. Once trained, the model is evaluated on the test dataset, with its performance measured using standard metrics like accuracy, precision, and recall. The final model is deployed in a production environment, where it can process new satellite images and automatically detect objects such as roads, buildings, water bodies, and vegetation. A user interface is developed for visualizing the detected objects in the form of labeled bounding boxes, providing users with an intuitive way to interact with the system and analyze the results. The system can be further extended to generate reports or insights based on the detected objects, supporting decision-making in areas like urban planning, environmental monitoring, or disaster management.

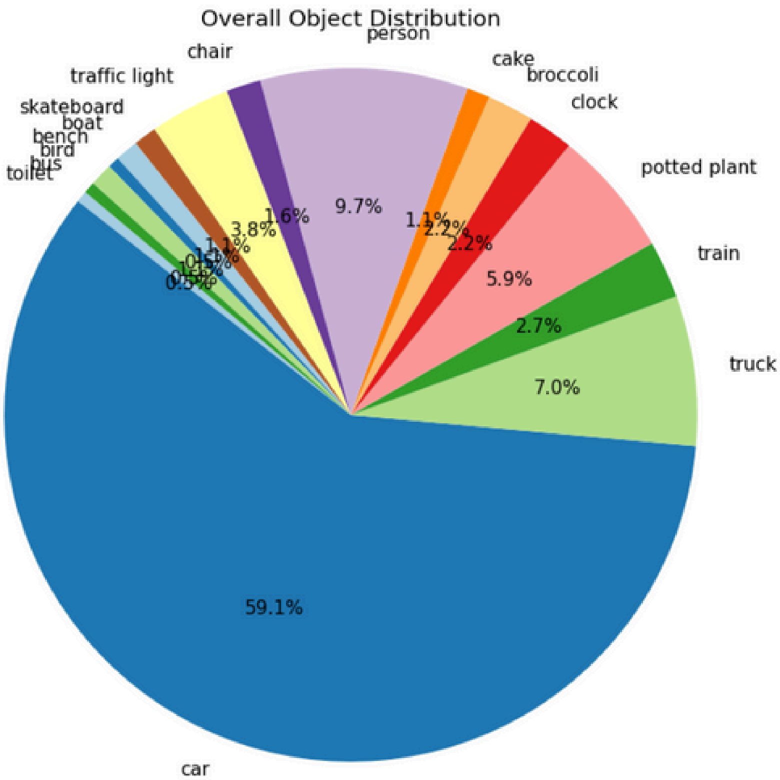
OUTPUT


train_metrics.py 9+, U
metrics_callback = MetricsCallback(validation_data=validation_dataset)
# Train your model with the callback
model.fit(
train_dataset, # Training data
epochs=10,
validation_data=validation_dataset, # Validation data
callbacks=[metrics_callback] # Pass the callback to the training process
)
# After training, plot the metrics
metrics_callback.plot_metrics()
PROBLEMS 17 OUTPUT DEBUG CONSOLE TERMINAL PORTS COMMENTS
35/35 34s 985ms/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00
Epoch 5/10
1/1 0s 168ms/stepep - accuracy: 1.0000 - loss: 0.0000e+00
Epoch 5 - Accuracy: 0.8176, Precision: 0.5424, Recall: 0.8843, F1: 0.9395
35/35 41s 985ms/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00
Epoch 6/10
1/1 0s 170ms/stepep - accuracy: 1.0000 - loss: 0.0000e+00
Epoch 6 - Accuracy: 0.9238, Precision: 0.7038, Recall: 0.8380, F1: 0.7388
35/35 26s 734ms/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00
Epoch 7/10
1/1 0s 190ms/stepep - accuracy: 1.0000 - loss: 0.0000e+00
Epoch 7 - Accuracy: 0.9763, Precision: 0.9524, Recall: 0.6471, F1: 0.9529
35/35 26s 731ms/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00
Epoch 8/10
1/1 0s 208ms/stepep - accuracy: 1.0000 - loss: 0.0000e+00
Epoch 8 - Accuracy: 0.5695, Precision: 0.5314, Recall: 0.8870, F1: 0.9392
35/35 26s 735ms/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00
Epoch 9/10
1/1 0s 159ms/stepep - accuracy: 1.0000 - loss: 0.0000e+00
Epoch 9 - Accuracy: 0.5064, Precision: 0.6961, Recall: 0.8644, F1: 0.5439
35/35 26s 736ms/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00
Epoch 10/10
1/1 0s 155ms/stepep - accuracy: 1.0000 - loss: 0.0000e+00


Metrics over Epochs
Accuracy
Precision
Recall
F1 Score
Metric Value
Epochs
1.0
0.9
0.8
0.7
0.6
0.5
2
4
6
8
10



person: 18
cake: 2
person: 18
chair: 3
traffic light: 7
chair: 3
traffic light: 7
skateboard: 2
boat: 2
bench: 1
bird: 2
traffic light: 7
skateboard: 2
boat: 2
bench: 1
bird: 2
skateboard: 2
boat: 2
bench: 1
bird: 2
bus: 1
Generating pie chart...
bench: 1
bird: 2
bus: 1
Generating pie chart...
bus: 1
Generating pie chart...
Sizes: [1, 110, 13, 5, 11, 4, 4, 2, 18, 3, 7, 2, 2, 1, 2, 1]
Pie chart saved as pie_chart.png



Overall Object Distribution
person
chair
traffic light
skateboard
boat
bench
bird
bus
toilet
cake
broccoli
clock
potted plant
train
truck
car
9.7%
3.8%
1.6%
2.2%
5.9%
2.7%
7.0%
59.1%

CONCLUSION

In conclusion, the proposed system demonstrates the potential of combining Hybrid Graph Convolutional Networks (GCN) with Capsule Networks to enhance object detection in satellite imagery. By leveraging graph-based feature extraction and the spatial hierarchy of capsule networks, the system significantly improves the accuracy and robustness of detecting complex objects such as roads, buildings, and natural features. The integration of these advanced techniques allows for full automation of the object detection process, eliminating the need for manual annotations and making the system highly scalable. The deployment of the model in a real-world application further demonstrates its practical utility, offering a user-friendly interface for visualizing and analyzing detected objects. This system not only contributes to advancements in satellite image processing but also has broader implications in fields such as urban planning, environmental monitoring, and disaster response, providing a powerful tool for automated analysis and decision-making.

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