SATELLITE IMAGERY & AI FOR INFRASTRUCTURAL CONDITION & MAPPING

[1,*]SOHAN R VERNEKAR , [2,*]LIKITH H , [3,*]MALLIKARJUNA R , [4,*]MANOJ N , [5,*]THANMAY RAM

UG Scholar, Department of Computer Science and Technology Dayananda Sagar University, Bangalore, India

sohanvernekar61@gmail.com , likhith22ab@gmail.com , mkallyam.2002@gmail.com , manoj12naik2003@gmail.com , thammayram1834@gmail.com

+91-8747041855 , +91-7676741824 , +91-6362736296 , +91-9964693507 , +91-9121611677

[1,*] Corresponding Author

[5,*] SANTHOSH KUMAR J

Assosciate Professor, Department of Computer Science and Technology Dayananda Sagar University, Bangalore, India

santoshkumar-ct@dsu.edu.in

+91-9035636616

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.

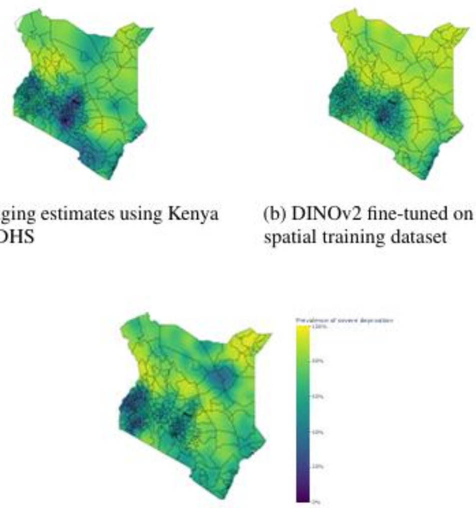
Keywords – Sustainable Urban Development , Satellite Imagery , Convolutional Neural Networks (CNNs) , Data-Driven Insights.

I. 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.

II. LITERATURE SURVEY

The use of satellite imagery in various domains such as agriculture, health, urban planning, and environmental monitoring has garnered significant attention in recent years, with advancements in deep learning techniques greatly enhancing the analysis and interpretation of these images. A range of studies has explored the use of satellite data combined with other resources, such as demographic and health surveys, to derive meaningful insights. For instance, one notable study paired satellite imagery with high-quality survey data on child poverty to create a new benchmark dataset, focusing on spatial and temporal generalization. The dataset includes satellite images spanning 19 countries across Eastern and Southern Africa, aimed at evaluating models' ability to generalize over unseen locations and data beyond the training years. This innovative benchmark was used to test a variety of models, from low-level models like MOSAIKS to more sophisticated deep learning architectures such as Self-Distillation with no Labels (DINOv2) and Sat MAE. These models showed promise in deriving meaningful insights from satellite imagery, though the field is still developing and faces challenges in addressing the unique characteristics of satellite images, including variations in spatial resolution and spectral heterogeneity.



(a) Kriging estimates using Kenya 2022 DHS

(b) DINOv2 fine-tuned on KidSat spatial training dataset

(c) DINOv2 fine-tuned on KidSat temporal training dataset

Fig 1 : Estimates of the prevalence predictions of several models

In the realm of object tracking, specifically Single Object Tracking (SOT) in satellite videos, traditional bounding box-based trackers have been less effective due to the small size and dynamic nature of the targets. Satellite imagery, with its often unpredictable and complex backgrounds, poses significant challenges for traditional tracking methods. While bounding box-based trackers work well in controlled environments, they struggle with the diverse and cluttered backgrounds typical in satellite videos. Point-based trackers, however, show promise in addressing these challenges by focusing on individual features or points within the image, offering more precision and adaptability. Existing approaches to object tracking in satellite imagery often employ adaptations of generic visual tracking algorithms, with a focus on motion models or region-based tracking. However, these methods tend to be less robust, especially when dealing with low-resolution and sparse object data.

Recent innovations aim to overcome these limitations by integrating machine learning techniques and leveraging prompt engineering strategies. One such approach involves the use of the Segment Anything Model (SAM) and TAPIR (Tracking Any Point with per-frame Initialization and Temporal Refinement) to improve tracking performance in satellite imagery. SAM's segmentation capabilities provide precise initial inputs, which are then refined through TAPIR's per-frame initialization and temporal refinement techniques.

This combination helps address background variations and the low-resolution nature of satellite objects, resulting in enhanced object tracking performance. The method's adaptability and effectiveness have been validated through experiments on datasets like VISO, showcasing its potential to handle the unique challenges posed by satellite imagery.

While the field continues to evolve, these studies highlight the growing potential of combining machine learning techniques with satellite imagery to improve object detection, tracking, and analysis. However, challenges such as background variability, resolution discrepancies, and the need for robust models that can generalize across different environments remain areas of ongoing research.

III. 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), Res Net, 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.

IV. PROPOSED METHODOLOGY

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, Res Net, 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 (Caps Net) in our model allows for hierarchical feature extraction. Caps Nets 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

V. DATASETS

The datasets used in this project were sourced from Kaggle, specifically the Space Net dataset. Space Net provides high-resolution satellite imagery, which is ideal for tasks such as object detection, classification, and segmentation. The dataset contains labeled satellite imagery of cities and regions, including buildings, roads, and other objects. It is often used in remote sensing tasks, such as urban planning, disaster response, and geographic information systems (GIS). The images in the Space Net dataset are typically annotated with ground truth data, which allows for supervised learning and evaluation of models in a real-world context. By using this dataset, the project can leverage state-of-the-art deep learning techniques for tasks like detecting roads, buildings, and other urban structures, providing insights into the capabilities of the chosen model architectures.

VI. EVALUATION METRICES

The evaluation of the proposed method was primarily based on **Intersection over Union (IoU)** between the predicted segmentation masks and the ground truth masks.

Given a known ground truth mask AA and a predicted mask BB, the IoU is calculated as:

$$\text{IoU}(A,B) = \boxed{\frac{A \cap B}{A \cup B}}$$

This metric measures the overall overlap between the true region and the predicted region, which is crucial for evaluating the accuracy of segmentation tasks. In our approach, a true detection is considered when the IoU is greater than or equal to 0.5, indicating that there is at least a 50% overlap between the predicted mask and the ground truth mask.

We then define the following parameters to evaluate the performance:

Precision (IoU ≥ 0.5): Precision is calculated when the IoU is greater than or equal to 0.5, defined as:

$$\text{Precision}(\text{IoU}\geq 0.5) = \frac{TP_{\text{IoU}\geq 0.5}+FP_{\text{IoU}\geq 0.5}}{TP_{\text{IoU}\geq 0.5}}$$

Where:

$TP_{\text{IoU}\geq 0.5}$ represents true positive predictions where the IoU exceeds 0.5

$FP_{\text{IoU}\geq 0.5}$ represents false positive predictions.

Recall (IoU ≥ 0.5) Recall is computed for the IoU threshold of 0.5, defined as ::

Where

$$\text{Recall}(\text{IoU}\geq 0.5) = \frac{TP_{\text{IoU}\geq 0.5}+FP_{\text{IoU}\geq 0.5}}{TP_{\text{IoU}\geq 0.5}}$$

$FN_{\text{IoU}\geq 0.5}$ represents false negatives when the IoU is less than 0.5.

Finally, the overall performance is summarized by two final scoring parameters:

Average Precision (AP): The average precision ($AP_{\text{IoU} \geq 0.5}$) is computed by averaging the precision values for all ground truth annotations at the IoU threshold of 0.5.

Average Recall (AR): The average recall ($AR_{\text{IoU} \geq 0.5}$) is computed by averaging the recall values for all ground truth annotations at the IoU threshold of 0.5.

These evaluation metrics—IoU, precision, recall, average precision, and average recall—are essential for assessing the performance of the proposed model in accurately identifying and segmenting relevant regions in satellite images or other datasets.

VII. INSTANCE SEGMENTATION USING CUSTOMIZED GCN & CAPSULE NETWORK

Evaluation of Instance Segmentation using GCN and Capsule Networks

As a first approach, we propose a two-stage solution for instance segmentation. The first stage is a **Graph Convolutional Network (GCN)**, followed by a post-processing stage using **Capsule Networks (CapsNet)**. The GCN stage learns graph-based feature representations of the image, while the CapsNet stage refines the predictions and captures the hierarchical spatial relationships between instances. The overall pipeline takes raw satellite imagery along with metadata as input and predicts the instance segmentation masks.

Customized GCN-based Neural Network : Inspired by recent works in deep learning, we implemented the **GCN** stage to capture global spatial relationships and enhance the model's ability to segment complex structures. The GCN learns node and edge-based features from the image grid, which are then passed to the Capsule Network for final segmentation prediction. The combination of GCN and Capsule Networks enhances the model's robustness to small or closely packed objects.

Loss Design : During initial experiments, we identified that small instances and closely packed objects (such as buildings) were particularly challenging for the model. These instances are crucial for accurate evaluation as metrics like **Average Precision** (AP) and **Average Recall** (AR) treat all instances equally, including small ones. To address these challenges, we designed a custom loss function incorporating two factors:

Distance-weighting: The first factor assigns higher weights to pixels closer to other objects to help the model distinguish between closely located instances.

Size-weighting: The second factor assigns higher weights to small objects to ensure that small instances are accurately segmented, despite their limited pixel coverage.

The custom loss function is defined as follows

$$Loss(x,y)=W\cdot(W_d\cdot Loss_{ce}+W_s\cdot Loss_{dice})$$

Where:

- x represents predictions from the model,
- y is the ground truth
- W_d W_s_ are the distance and size weights, respectively,
- **$Loss_{ce}$** and **$Loss_{dice}$** represent Cross Entropy Loss and Dice Loss, respectively.

This loss function enables the model to jointly optimize for both small instances and closely located objects, which significantly improved segmentation accuracy.

Training Scheme: The model is trained using a multi-stage training approach:

- Initialize with pre-trained weights,
- Train on a small subset of the dataset using a learning rate of 10−410^{-4},
- Fine-tune on the full dataset and adjust the learning rate during training to improve convergence and model performance.

The training scheme, along with the custom loss function, helped the model achieve improved **Average Precision** (AP) and **Average Recall** (AR) values.

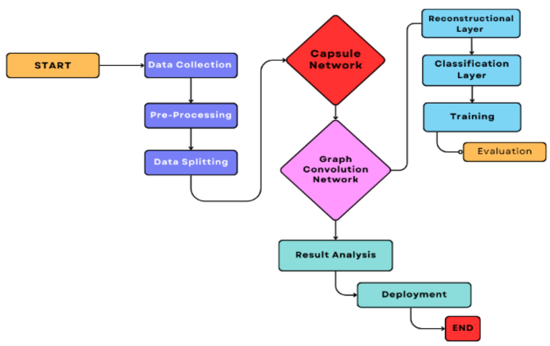


Fig 2 : Depciting The Flowchart & Methodology

VIII. PRE – PROCESSING

Preprocessing of the training data involved **padding images to 320×320** resolution using reflective padding, which helped increase the visible area of objects and prevented cutting off building parts at the edges and corners of each tile. The ground truth annotations, initially in polygon format, were converted to **binary pixel masks** for consistency in training, ensuring the masks aligned with the model's output.

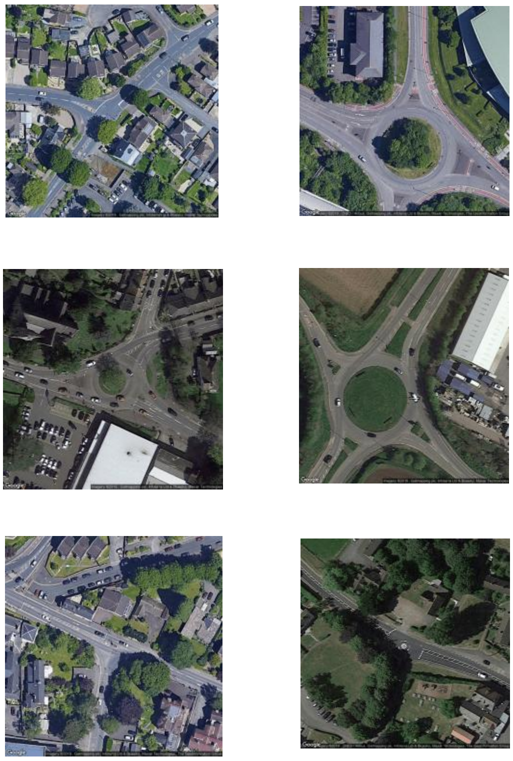


Fig 3 : Different Types of Datasets Used for Pre-processing & Training

The dataset underwent **augmentation** to improve generalization and robustness of the model.

The augmentations included **random horizontal/vertical flips**, **90° rotations** within a ±4° range, and slight adjustments to **brightness and contrast** of the images. These augmentations were essential for introducing variability in the input data and preventing overfitting to the training set.

IX. TRAINING

The loss function used in our approach is a weighted combination of **Cross-Entropy Loss** and **Dice Loss**, which was empirically found to yield better results than using either loss alone. This combination ensures that the model is penalized both for misclassification (via Cross-Entropy) and for poor segmentation (via Dice Loss), leading to more accurate instance segmentation predictions We trained the model using a **1-cycle learning rate schedule**, a strategy introduced by Leslie Smith (Leslie and Topin, 2017) to achieve faster convergence with higher learning rates.

	No:of Epochs	Training Time	Accuracy	Recall	Precision
1 cycle only	10	84 ms /step	97.23	96.14	95.01
1 cycle and cylindrical learning rate X 2	50	94 ms/step	98.34	97.56	96.45

Table 1 : Representing The Training Table of the Datasets Fig 2

This method has been widely used in practical applications, such as in Stanford's **DAWN Bench competition** for training CIFAR-10 and ImageNet classification models. The **Fast.ai** library provides built-in support for **1-cycle training**, and its use in our experiments is well documented (Gugger, 2017b). The training process used a **batch size of 32**, and we employed the **Stochastic Gradient Descent (SGD)** optimizer with momentum. The initial phase of training involved **warming up the model** by training only the un-pretrained decoder layers for one epoch at a learning rate of 6. Afterward, we unfroze all the model weights and initiated the 1-cycle training for **10 epochs**. The learning rate was set to **0.15**, linearly increased to **6** by 45% through training, then linearly decreased back to **0.15** by 90%, and finally decayed to **0.0015** in the last 10% of the training process. During this, the momentum was scaled inversely with the learning rate to maintain stability. After the initial 1-cycle training, we continued the training with two

learning rate schedule, where the learning rate varied between **0.05** and **1** and back to **0.05** over each cycle. This helped further optimize the model and refine its predictions.

X. EXPERIMENTAL RESULTS

The proposed **GCN + Capsule Network** architecture was trained on the provided **satellite imagery dataset** following the training procedure outlined in Table 1. To determine the optimal parameters for the model, we varied key threshold values and tested different configurations of the network. Specifically, we adjusted the **threshold (θ)** values between 0.3 and 0.8 to find the most effective setting for instance segmentation. Additionally, we explored various network depths and configurations to evaluate how they impacted performance. While pixel-wise accuracy remained high due to the dominance of background pixels, we observed that misclassified pixels caused a decrease in both precision and recall metrics. An overview of the final results is presented in **Table 1**, showing the performance of the models across different configurations and threshold values.

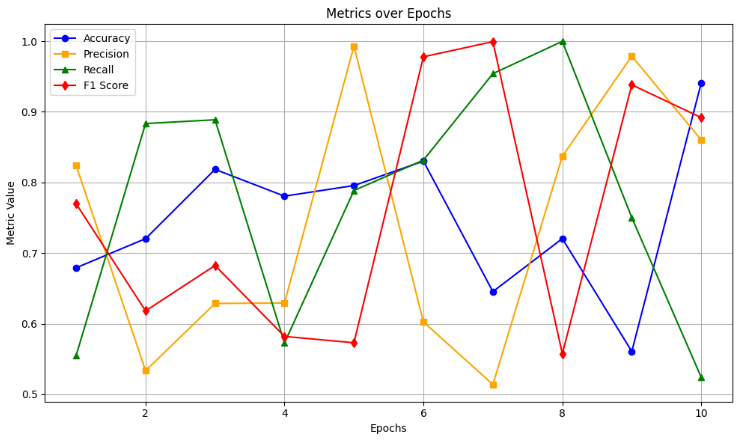


Fig 4 : Depciting the results over 10 & 50 epochs

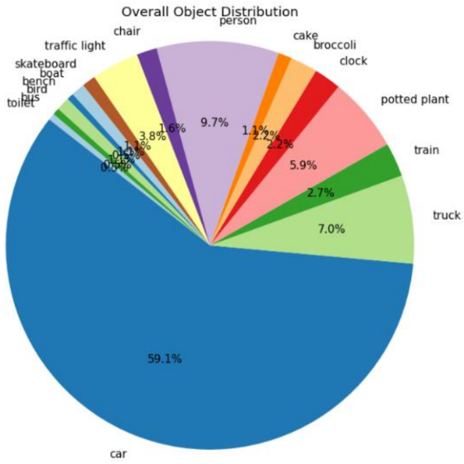


Fig 5 : Decipting The Pie Chart of Object Detection

The final evaluation results were obtained on the official test dataset, with key performance metrics such as **Average Precision (AP)** and **Average Recall (AR)** calculated for all configurations. We evaluated the model with various depths and configurations, such as **Net8**, **Net10**, and **Net12**, with a threshold value (θ) of 0.5. These results indicate that increasing the number of GCN layers and Capsule network blocks led to improved precision in detecting smaller objects and distinguishing instances, which demonstrates the architecture's ability to handle complex spatial patterns in satellite imagery. The additional training focused on optimizing instance boundaries and improving segmentation quality with small and closely packed objects, which resulted in small but noticeable improvements in segmentation precision and recall. As reported in **Table 1**, the final performance on the held-out test set achieved an **AP** $_{\mathbf{IoU \geq 0.5}}$ of **0.925**, and an **AR** $_{\mathbf{IoU \geq 0.5}}$ of **0.948**.

XI. 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

XII. REFERENCES

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