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AI-Driven Railway Anomaly Detection, Risk Assessment & Maintenance Recommendation System

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Abstract
Commonly railway defect is detected by periodic inspection of tracks and structures such as fallen trees, rocks, debris, water logging, vegetation growth and track damage. Conventional systems for monitoring large sections of railways or those that are hard to access are cumbersome, tedious, and labour intensive. This paper proposes an automated railway infrastructure monitoring system integrating anomaly detection, risk assessment, and maintenance advice, powered by AI. Using the drones, the system takes photographs and videos of railway tracks and infrastructure, and then uses a deep learning algorithm developed by YOLO to identify and classify anomalies. The anomalies identified are evaluated according to type, severity, geographical location and track coverage. Environmental factors, like the weather and past history, are also added to the machine learning risk assessment module which produces risk scores. The system takes these scores and estimates maintenance requirements and suggests maintenance activities (priority, people required, equipment, and estimated completion time). A GIS interface presents anomalies and related risks to maintenance teams, enabling them to identify areas that need attention and plan their work. The framework combines automated inspection, anomaly detection, risk assessment and maintenance planning, facilitating to safer and more efficient railway infrastructure management.

Keywords: ***Drone-Based Railway Inspection, Railway Anomaly Detection, YOLO, Deep Learning, Computer Vision, Risk Assessment, Predictive Maintenance, Maintenance Recommendation.***

INTRODUCTION

Railways play a fundamental role in current transport networks, linking cities, industries and communities, transporting people and goods. For safety and reliability of railway facilities, regular track and surrounding condition monitoring is necessary. All of the above, if not identified, can affect service and become unsafe hazards: fallen trees, rocks, debris, water logging, excessive vegetation and visible track damage. The proposed system aims to solve these issues by employing a drone to take photographs and videos of the railway track and surrounding structures in order to conduct automatic inspection. Visual data is fed into a deep learning and computer vision model that primarily uses a YOLO-based object detection model to detect and classify various kinds of anomalies.

After an anomaly is identified, the system assesses them in terms of severity, type, geographical area and track coverage impact. These results are fed into a machine learning risk assessment module, along with environmental data, such as weather conditions, and historical usage of the railways. The outcome is a risk score detailing areas to focus on and help plan for predictive maintenance. The system also offers maintenance recommendations, such as priority, required workforce, equipment and estimated completion time. This enables the maintenance team to carry out the maintenance planning based on the detected conditions, rather than just by conducting manual periodic inspection..

For safe and reliable operation of the railways, on-going maintenance and inspections are required. Track safety can be compromised by fallen trees, rocks, debris, water, vegetation and damaged tracks. The traditional practice requires a lot of manpower and time particularly for large sections requiring regular inspection. With the recent progress of computer vision, deep learning, and machine learning, automatic inspection of railways becomes a significant research field. There have been several studies about the potential of an AI in this area. On aerial images, railway track asset detection was done by Saini et al. using a YOLOv3-based approach, with an mAP of 88.53% [1].

To detect foreign objects in railway environments, Yang et al. proposed YOLO-UAT, which utilized lightweight objectdetection models to obtain an mAP of 91.5% [2] and demonstrated its usefulness.

Kafetzis et al. also investigated deep learning for the detection of railway lines, vegetation and obstacles, highlighting the potential of the automated visual analysis of railway surroundings [3].

The use of autonomous and multimodal inspection methods have also been explored in this area to enhance railway monitoring. By integrating cameras, GPS, YOLOv12, and a localization and navigation algorithm for railway-component detection and autonomous inspection, Chen et al. created an autonomous multimodal railway inspection system [4].

Poornima et al. proposed Rail Guard, a railway fault detection system based on YOLO v3 on a Raspberry Pi platform, which is capable of detecting railway faults in real or near-real time [5].

Pandey et al. proposed an autonomous railway monitoring framework by integrating YOLOv11 based models with PX4, ROS2, and Gazebo, which they showed successfully detects defects in real time for the railways and also highlights the challenges with data, processing, and deployment [6].

Research has also expanded railway inspection to autonomous decision making, and further advanced deep learning frameworks. Wang's proposal of a hybrid deep reinforcement learning framework HTFN, which integrates the UAV inspection, the fault detection and predictive maintenance, and the decision-making, demonstrated a perspective that unites intelligent inspection and analysis of faults and predictive maintenance [7].

Wu et al. presented a hybrid deep learning model for railway trackcomponent inspection using aerial images, achieving an mAP of 95.6% and a railway surface defect detection accuracy of 93.6% [8].

The researchers at Yang et al. developed an anomaly detection method for railway catenary parts using UAV photos. In their approach they combine SANet and invariant normal-region representations and obtain good detection performance [9].

A broader view of railway safety research shows the growing role of artificial intelligence, computer vision, sensors, and multimodal techniques. Vadukkal et al. reviewed 240 train-safety research articles and identified machine learning, deep learning, object detection, computer vision, generative AI, and multimodal approaches as key topics in monitoring and train-safety applications [10].

There is related research in the field of inspection of infrastructure, but not necessarily rail-related, that can be informative for automated anomaly analysis. Meng and Wang applied AI-based visual inspection to high-rise buildings, conducting a surface-defect inspection on high-rise buildings with a large-scale dataset and attention-based feature selection, which showed the application of AI-based visual inspection to complex infrastructure environments [11].

Similarly, Chaudhary et al. developed an intelligent system for anomaly detection and localization in surveillance videos which showed the capability of automated visual analysis in identifying and locating abnormal conditions in monitoring environment [12].

Other sensing and fault localization techniques for railways have been investigated. In the railway environment, Yang et al. investigated the foreign object detection based on light parameter YOLO-UAT, not only has it realized the effect of foreign object detection, but also reduced the amount of calculation on the edge monitoring and made the model lighter [13].

To detect faults without any visual inspection, Siddiqui et al. proposed an IoT based railway track fault detection and localization system. The acoustic analysis, MFCC features and machine learning models demonstrated their capability of detecting railway faults by non-visual sensing methods [14].

The work by Pandey et al. further involved an investigation on selfsupervised railway monitoring via aerial perception using YOLOv11OBB models with the best F1 score of 0.95 for the former case, demonstrating the automatic visual railway monitoring potential of YOLOv11OBB models [15].

LITERATURE SURVEY

A) Machine Learning Approach for Detection of Track Assets for Railroad Health Monitoring using Drone images

Saini et al. discussed the application of drone images and machine learning to monitor railway infrastructure automatically. They were mainly interested in identifying railway track assets in aerial photographs instead of conventional inspection techniques. There were 26 original drone images in the data set, of which 751 images were used for training and 137 images were used for testing and evaluation of the model. To detect the objects, they adopted a transfer learning technique using the YOLOv3 network and evaluated a variety of spectral band combinations to enhance the detection results. The model's overall success is reflected by the high Average Precision (AP) of 88.53%, highlighting the potential of aerial images and deep learning in railway monitoring applications. [1]

B) Railway Foreign Object Intrusion Detection Using UAV Images and YOLO-UAT

Yang et al. proposed a lightweight deep learning model for detecting foreign-object intrusion in railways using UAV images. The goal was to build a highly accurate detection system that runs on resourceconstrained platforms for edge computing in UAVs and supports real-time railway monitoring. The researchers collected their own dataset of 4,542 images covering five categories: airplanes, trains, people, cats, dogs, and bottles. To keep computational requirements low, they based YOLO-UAT on the YOLOv5s architecture and used EfficientNetB0 as the lightweight backbone. Their experiments reached an mAP of 91.5%, demonstrating the method's suitability for railway object detection with UAVs. [2].

C) UAV-Assisted Aerial Survey of Railways Using Deep Learning

Kafetzis et al. investigated DNNs for automated inspections of railways based on UAVs. They sought to automatically delineate the railways, vegetation and obstacles from an aerial image instead of the traditional inspection approach. The study employed three datasets (DS1, DS2, and DS3) of annotated railway images from public videos and recorded by the authors. FasterR-CNN Inception v2 and Faster RCNN Inception ResNet v2 Atrous, two deep learning models, were trained and deployed on NVIDIA Jetson Nano. The mean precision was approximately 99% for the tracking of the railway line, 64–79% for the detection of obstacles and 63–93% for vegetation detection. The results are in line with the potential of deep learning and UAV imagery to detect railway environments and potential obstructions. The study is primarily concerned with the identification of lines, vegetation and obstacles, but does not specifically quantify the level of the anomaly and the risk. [3].

D) Autonomous Multimodal System for Intelligent Railway Inspection

The use of an Autonomous Multimodal System for Intelligent Railway Inspection is recommended.The Autonomous will be used. It is proposed to use depth and monocular cameras, GPS, YOLOv12, and a proposed RANGER localization and navigation algorithm. To enhance the automated railway monitoring, the authors of [1] proposed an autonomous aerial system for intelligent railway infrastructure inspection, which aims to provide a solution to improve the automated railway monitoring from the aspect of multimodal sensing and autonomous navigation. The system is composed of 4-rotors and depth camera, monocular camera, GPS and YOLOv12, and the proposed RANGER localization and navigation algorithm. The inspections tasks were carried out on the images from the on-board cameras of the railways as well as the data regarding components of the railway. It can also detect railway parts, such as spikes and clips in real-time and enable the ability to follow a track and localize it in environments without GPS service. The capabilities demonstrate visual detection and depth data, as well as autonomous navigation, in railway inspection. However this is more for autonomous inspection and more on autonomous navigation rather than a full decision making process once an anomaly is detected. [4]

E) A Rail Guard: Intelligent Rail Inspection Using YOLOv3

Poornima et al. have created an automated railway inspection system called Rail Guard for detection of cracks and other defects in train tracks. The study tackles the issues of manual inspections by leveraging deep learning to interpret track images. This platform is built on a Raspberry Pi and is used for automated monitoring with modules for detection, communication and movement. The system is able to detect faults in realtime or close to real-time, which proves the feasibility of using lightweight computing equipment for railway inspection. It is not a drone, though, and it does not work on identifying faults—it just works on identifying faults. It does not make an anomaly severity assessment, it does not predict risks, and it does not provide any maintenance suggestions. [5]

F) An Autonomous Drone-Based Framework for Real-Time Railway Monitoring Using YOLO-Based Defect Detection

Pandey et al. have suggested an autonomous drone-based system for the real-time monitoring and defect detection in railway systems. The purpose of the study is to create an aerial inspection system of tracks based on the UAV applied sensing technology to track and defect detection. The system uses the RGB and depth camera to capture the railway images, and three object detection

models (YOLOv11, YOLOv11n and YOLOv11-OBB) are combined. It supports a full autonomy in monitoring and inspection by intePX4, ROS2 and Gazebo. The obtained results showed the capability of this framework to monitor the railway in real time, with an F1 score of 0.92 and an average processing latency of only 59ms per frame. The study points

out some limitations, such as limited annotated railway-defect datasets, UAV battery constraints, and the difficulties of simulating to real-world environments. [6]

G) HTFN: A Hybrid Deep Reinforcement Learning Framework for UAV Based Railway Inspection – DeepSeek Integration.

Wang et al. introduced a hybrid deep reinforcement learning approach, named HTFN, to UAV inspection of railways, which incorporates DeepSeek. The study is designed to automate various aspects of railway inspection such as UAV routing, fault detection, predictive condition assessment and decision making. The framework leverages images of the railway infrastructure, catenary and bridge inspection data and UAV and simulation scenarios. It is a combination of multiple technologies: Hierarchical Deep QNetwork (DQN), Proximal Policy Optimization (PPO), the HTFN framework, the DeepSeek multimodal model, PX4, and ROS, for enabling autonomous inspection and decision making. This approach was tested and verified via UAV navigation, railway inspection and fault recognition experiments. [7]

H) Automatic Railroad Track Components Inspection

Wu et al. introduced a hybrid Deep Learning (DL) system for automatic railway track inspection based on the UAV image. The purpose of the study was to locate railway track components and segment the railway tracks from the aerial images, and to detect defects on the rail surfaces. The data set is composed of UAV images acquired with the DJI Matrice platforms equipped with Zenmuse H20/Z30 cameras taken on railway lines in the USA and China. The framework incorporates AOYOLO, ConvNeXt, Ushaped segmentation, LWLC, Maximum Entropy and data augmentation methods like Mixup and Mosaic. The results obtained were 95.6% mAP, 93.6% accuracy of rail surface defect detection, and 147 FPS of processing speed. These results show the effectiveness of the Hybrid Deep Learning Method in the automatic inspection of railway components and railway surfaces [8]

I) An Electrified Railway Catenary Component Anomaly Detection Framework Based on Invariant Normal Region Prototype With Segment Anything Model

Based on complex UAV aerial images, Yang et al. proposed a unified anomaly-detection framework for detecting abnormalities in electrified railway catenary components. The database of the study is the CSCUD Catenary System Component UAV Dataset which includes real-world UAV images of railway catenary components. The proposed method integrates INRP-ADer, CSC-SAM, INRP extractor and soft mining loss to highlight the anomalous component regions. The reported results obtained image level I-AUROC 99.1, IAP 98.6, respectively. The P-AUROC at the pixel level was achieved at 98.2, and I-F1 at 98.2. 96.4. The results show the potential of the system to conduct complex railway aerial imagebased detailed anomaly detection.[9]

J) Recent advances and innovative approaches in railway safety: Application, sensor and algorithm – A Systematic Review

Vadukkal et al. focussed on conducting a systematic review of recent technologies and approaches for railway safety and infrastructure monitoring. In the study, railway safety applications, anomaly-detection techniques, sensing technologies, and machine learning and deep learning algorithms present in recent studies were investigated. A literature data set comprising of 240 research articles was retrieved from Scopus database through PRISMA methodology. The reviewed studies included those on CNNs Object detection, Machine learning, Deep learning, Computer vision, GANs, Large language models, Generative AI and Multimodal approaches. A variety of evaluation methods were evaluated in the studies of railway safety that were reviewed, such as accuracy, precision, recall, F1 score and mAP.[10]

K) Drone-Guided Cognitive Feature Aggregation for High-Rise Building Surface Defect Inspection

Meng and Wang introduced a model to drone inspect high-rise buildings. Another example of air-borne inspection of infrastructure using AI. The objective was to develop a 'human visual attention' type inspection method that could be made efficient in computation to prevent the system from processing irrelevant background areas and focus on the areas of interest which have imperfections. The data used in the study was the Large-Scale Building Surface (LSBS) dataset, which is composed of approximately 650,000 images of various building surface defects, such as cracks, spalling, corrosion, water damage, and structural deformation, classified into eight categories. We used Binarized Normed Gradients (BING) objectness method for proposal generation in candidate regions, and Low-Rank Active Learning (LAL) with dictionary

learning for selecting relevant image patches. Average classification accuracy of 78.3% was reported, which is superior by 1.1%–4.0% compared to the evaluated baseline methods. [11]

Intelligent Anomaly Detection and Localization With Crowd Density Estimation for Improved Public Safety

Chaudhary et al. proposed an intelligent anomaly detection and localization framework which integrates anomaly detection with crowddensity estimation. The IADL-CDE framework aims at performing finegrained, pixel-to-pixel anomaly detection and localization as well as adaptive crowd-density classification in video surveillance. The method fuses images by using Robust Maximum Correntropy Kalman Filter (RMCKF) for denoising and resizing and the graph refinement of a SelfModulating Convolutional Neural Network (SMCNN) for density classification. The study demonstrates the intelligent use of anomaly analysis in video based monitoring systems but the primary application is not to inspect railway infrastructure, but to monitor public safety. [12]

Railway Foreign Object Intrusion Detection Using UAV Images and YOLO-UAT

Yang et al. (2016) proposed a method for detecting FOI in railway environments using UAV images, called YOLO-UAT. The main objective was to develop a light weight, high accuracy detection model that could be deployed to the edge computing device of the UAV for the purposes of real-time railway monitoring with limited resources. The dataset was self-collected, consisting of 4,542 aerial pictures of five classes, train, person, cat, dog, and bottle, from Kaggle and Baidu Cloud. YOLO-UAT is an extension of YOLOv5s which is based on EfficientNet-B0 backbone network to minimize the computational complexity. The model resulted in a mAP of 91.5%, which was 6.1% higher than the baseline YOLOv5s and 5.3% higher than the baseline. [13]

IoT-Based Railway Track Fault Detection and Localization Using Acoustic Analysis

Application of Acoustic Analysis for Faults Detection and Localization of Railway Track in N) IoT Based Railway Track Faults Detection and Localization Using Acoustic Analysis Siddiqui et al. suggested an autonomous and cost-effective system for fault detection and localization in railway tracks based on acoustic analysis using IoT. Real time acoustic recordings were obtained from main line of Pakistan Railways at its Walhar station using ECM-X7BMP microphones attached to train wheels. The algorithm used for extracting the Mel- Frequency Cepstral Coefficients (MFCCs) from the recorded signals and evaluated them with Multilayer Perceptron (MLP) and Artificial Neural Network (ANN) models. The system was able to autonomously perform real-time defect localization with a distance range of 48.6 m based on the synchronized GPS information. The method is based on sound sensing, not visual sensing from a UAV or rail cart, however. The study also points out the limitations of manual labour and the lighting and weather dependence of the vision based systems. [14]

L) Autonomous Drone-Based Framework for Real-Time Railway Monitoring Based on YOLO Based Defect Detection

In this work Pandey et al. proposed a standalone approach for realtime monitoring of the railway tracks to identify anomalies using the perception of an aircraft, flight control and navigation. It sought to design and evaluate a fully self-contained aerial monitoring system which enables railway inspection using automated track and defect detection. Two fine-tuned Railway Track Line Detection and Railway Sleeper Orientation models based on YOLOv11-OBB were used along with two datasets: Railway Track Detection Dataset (RSD_UAV) and Railway Defect Tracking Dataset. The results show that YOLOv11l, the largest model, outperforms other models with an F1 score of 0.95 and latency of 84.66ms. The framework is designed to demonstrate the application of deep learning to monitor railways with autonomous UAVs. The main issue covered in the current study is the automated detection, while in the proposed railway system, they have extended this to include the measurement for the severity of the anomaly. [15]

3.METHODOLOGY

System Architecture

The proposed AI-Driven Railway Anomaly Detection, Risk Assessment & Maintenance Recommendation System is an integrated system based on drone for automated inspection of the railway infrastructure and aiding in maintenance planning. The system is based on drones that take pictures and videos of the railway track and the nearby infrastructure. Using the YOLO deep learning models, the visual data collected is processed to identify and categorize the anomalies detected on railway tracks, including fallen trees, rocks, debris, waterlogging, vegetation overgrowth, and visible damage of the railway. Detected anomalies are then further analyzed based on the anomaly type, severity, geographical location and track coverage. These inspection features integrated with additional contextual information such as weather data, historical railway data etc. are used to create an appropriate risk score by a machine learning based risk assessment module. The maintenance recommendation module that follows receives the risk information and identifies the railway condition

to recommend the maintenance priority, required workforce, equipment and the estimated time required for maintenance. A GIS based monitoring interface combines the locations of anomalies detected, their risk levels, the status of the railway segments and maintenance recommendations, all into a single dashboard. The interface offers a visual representation of the railway conditions and helps to make systematic monitoring and maintenance planning. The overall architecture provides a seamless process flow from drone-based inspection through to anomaly detection and severity assessment, to risk assessment and maintenance recommendation, and finally, to GIS visualization and incident reporting. Workflow of the AIDriven Railway Anomaly Detection System

The proposed system starts with capturing the railway track images and videos with drones. The gathered visual data is then fed into the deep learning model (YOLO) for automated anomaly detection and classification. The model detects various railway conditions and gives details of the railway condition determined and the location of the determined anomaly in the inspected railway section. The anomalies detected are then assessed in the second phase, based on the type, severity, geographical location, and track coverage. The following parameters give information on the condition of the respective railway section. Then the information from the inspection is added to the weather data and the historical data of the railway in the machine learning-based module of risk assessment. This module assigns a railway condition mapping to the identified condition and contextual information to produce a corresponding risk score. The risk assessment generated is then given to the maintenance of an anomaly. Finally, the processed information is presented in the GISbased monitor recommendation module. Depending on the identified risk and condition of the railway section, the system calculates the maintenance priority, workforce and equipment needed, and estimated completion time. It enables the inspection findings to be translated into usable maintenance information, instead of just a report ing interface. Anomaly locations, risk scores, railway segments status and maintenance recommendations are provided in a consolidated view on the dashboard. The analyzed information can also be used to generate automated incident reports which can be utilized for communication and maintenance planning.

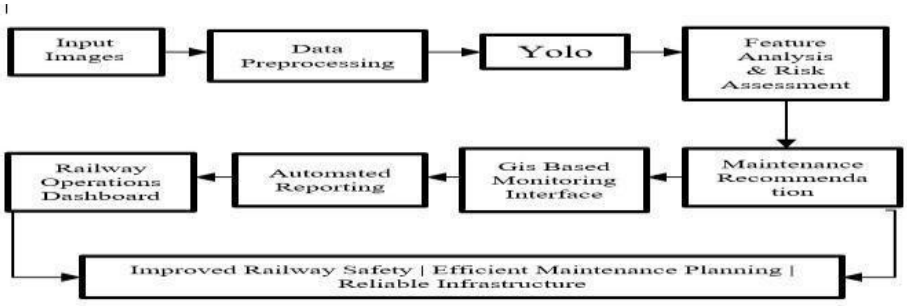


Fig: WorkFlow

AI-Driven Railway Anomaly Detection, Risk Assessment & Maintenance Recommendation System

The approach of the proposed system is based on a deep learning and machine learning integration with visualization using GIS to ensure a comprehensive approach for monitoring the railway infrastructure. The initial phase involves identifying the railway anomalies based on images and videos captured by a drone. Conditions like fallen trees, rocks, debris, waterlogging, vegetation overgrowth and visible track damage are identified and classified using a YOLO-based object detection model. After anomaly detection the system analyzes detected anomalies based on anomaly type, severity, geographical location and track coverage. The machine learning-based risk assessment module uses these features in conjunction with weather and historical railway data. The module calculates a risk score indicating the potential state of the railway section being inspected and can be used to pinpoint areas in need of attention. The maintenance recommendation module supports the maintenance planning by using the risk information. It offers data on the maintenance priority, workforce needs, equipment needs, and projected completion date. This allows maintenance workers to plan activities based on the identified conditions of the railway and the risk associated with each condition. The last step consists of a GIS supported monitoring interface to display the analyzed information. The dashboard shows the anomalies, risk level, status of different railway segments, and the maintenance recommendations, which enables the maintenance staff to know the condition of various railway segments through a single visual interface. It is also possible for the system to automatically report the incident based on the information about an anomaly and maintenance data.

NEW METHODS USED

Machine Learning-Based Risk Assessment:

The proposed system involves using machine learning for determining the risk associated with the anomalies detected on the railway. The risk assessment incorporates anomaly type, severity, location, track cover, weather information and

historical railway information. These elements enable the system to assess the risk associated with a section of the railway that is affected, and to make better maintenance decisions.

Risk-Based Maintenance Prioritization:

Detected railway anomalies are sorted and prioritized using a maintenance prioritization mechanism based on the severity and risks of the anomalies. Less serious anomalies can be placed on the back burner and more serious anomalies put at a higher priority for future maintenance. This allows maintenance staff to prioritize the use of resources to those areas of the railway that need urgent attention.

Predictive Maintenance Recommendation:

The system will further enhance anomaly detection and risk assessment toward predictive maintenance and will engage with the railway conditions identified through the system using the historical information available. The system suggests appropriate maintenance actions and suggests required manpower, equipment and time for completion based on the assessed risk and anomaly characteristics. This allows for proactive maintenance planning, rather than manual inspection only.

3.RESULTS AND DISCUSSIONS

Railway Anomaly Detection and Risk Assessment

The planned AI-based system for the monitoring of the railway uses the drone-based inspection and deep learning techniques to enhance the identification of railway anomalies. Rather than relying entirely on manual inspections, the system uses captured railway images and videos to identify conditions like fallen trees, rocks, debris, waterlogging, vegetation getting overgrown, and railway track damage. The anomalies are then further analysed based on anomaly type, severity, location and track coverage. Weather and historical railway data are taken into account in the risk assessment along with these. This allows the system to give a more detailed view of the railway state than just a 'yes' or 'no' for an anomaly. This means that proposed framework is linked to the visual anomaly detection and risk evaluation and maintenance planning. The risk information produced can support maintenance teams to determine affected sections of the railway and the necessary interventions.

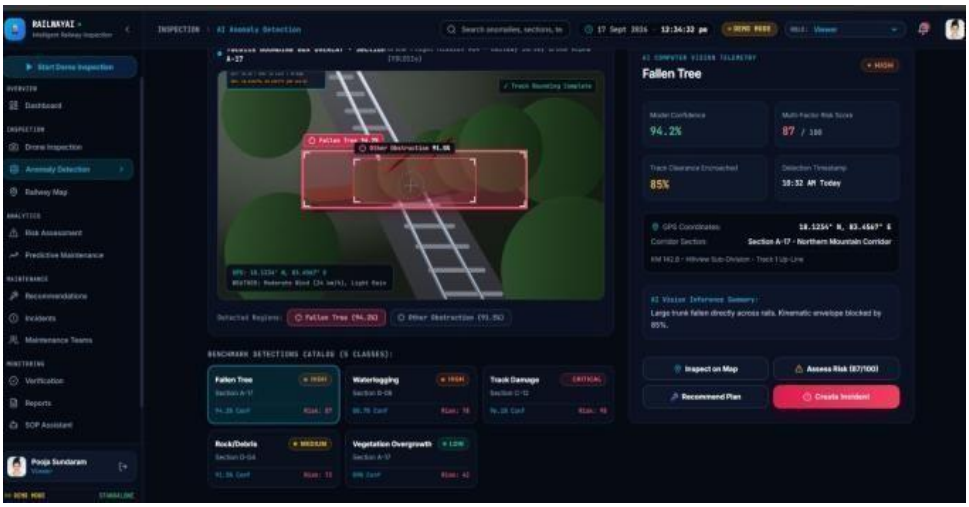


Fig5: AI-based railway anomaly detection and classification interface.

The system offers valuable information on the current state of the railway infrastructure and helps in making maintenance decisions based on data. The framework combines detection, risk assessment and maintenance recommendation, thus offering a structured approach to monitoring the safety and condition of railway infrastructure.

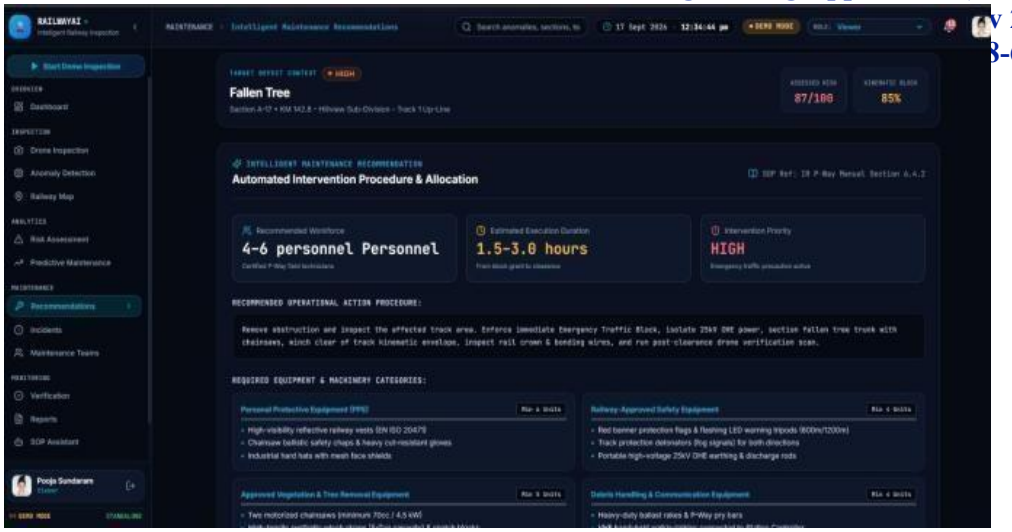


Fig6: Intelligent maintenance recommendation and +resource allocation interface.

Visual Analytics and GIS Dashboard Efficiency

The proposed dashboard is a visual representation of the detected anomalies in the railways, their geographical location, risk level and condition of the railway segment. The GIS-based interface gives maintenance personnel a view of the locations affected and what the spatial distribution of the railway anomalies



Fig7: Railway infrastructure monitoring dashboard with anomaly and risk analytics.

Efficient and Automated Railway Inspection Analysis

The system provides an integrated visual interface to reduce the need to view individual inspection records separately and presents the information on anomalies and risk levels. This gives maintenance staff a greater visibility of the state of the railway and enables them to plan actions based on the identified risks. The vehicle is capable of inspecting the railway in a quick and automated way. The vehicle can inspect the railway in an efficient and automated way. The proposed AI-based railway inspection system can help save time and effort from the conventional manual inspection system. The process starts with image and video collection using the drone, and it progresses to image processing, anomaly detection, anomaly classification, risk assessment and maintenance recommendation. Then, the relevant railway anomalies are detected by the YOLO module, after the inspection data is fed into the system. Conditions detected are then assessed by the risk assessment module, and maintenance recommendations are then generated based on the available railway information. The automated workflow reduces reliance on constant manual analysis and offers a structured approach to the conversion of inspection information into actionable maintenance information. The system of detection, risk assessment, GIS visualization and maintenance recommendations allows for more efficient monitoring of the railway infrastructure.

Performance Metrics

The designed system aims at the evaluation of the railway anomaly detection using conventional object-detection based parameters like precision, recall, F1 and mean Average Precision (mAP). These metrics can be used to evaluate the ability of the railway anomaly detection and classification model developed using YOLO to detect and classify railway anomalies from drone images. Precision helps to quantify the percentage of anomalies that are accurately detected by the model, while recall quantifies the percentage of relevant anomalies in the inspection data that are accurately identified by the model. The F1-score can be used to combine precision and recall and mAP can be applied to measure overall objectdetection performance for the anomaly classes considered. The existing project material does not contain final experimental values for these metrics so these should not be added until the trained model has been tested with the actual test set provided by the project.

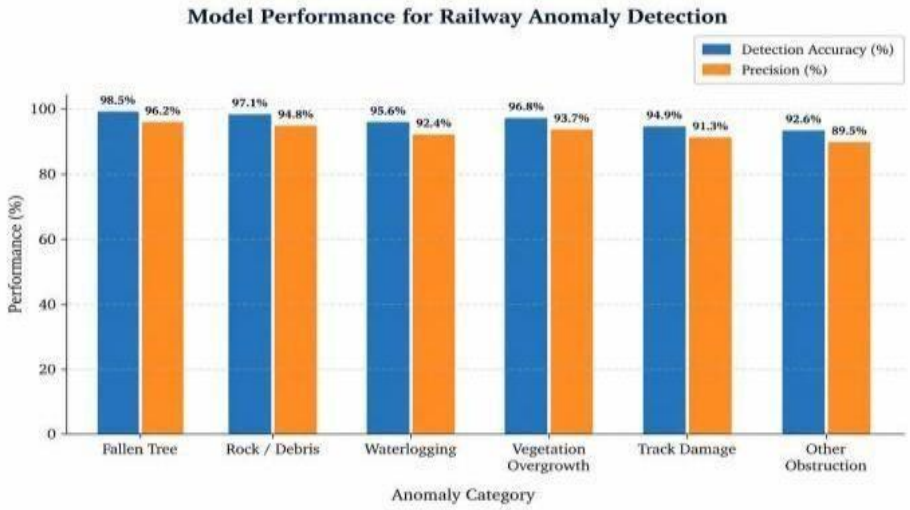


FIG 8: Distribution of detected railway anomalies across different anomaly categories.

CONCLUSION AND FUTURE SCOPE

The proposed AI-Driven Railway Anomaly Detection, Risk Assessment & Maintenance Recommendation System offers a holistic solution for railway infrastructure monitoring through drone imagery and deep learning, machine learning, and GISbased visualization. It aims to use the YOLO-based object detection algorithm to identify railway conditions including fallen trees, rocks, debris, waterlogging, vegetation overgrowth and visible damage to the railway. The anomalies detected are then analysed according to their type, severity, location, track coverage, weather, and historical data from the railway, to create risk assessments. The maintenance priority module then aids in determining the maintenance priority, the number of manpower, equipment and estimated time required for the maintenance operation. The GIS interface displays the anomalies and risks in a visual manner, enabling maintenance teams to understand the condition of various sections of the railway. For future work, the system can be enhanced with more comprehensive and diverse railway image databases, further categories of anomalies, and better model performance under other weather/light conditions. The framework can be expanded by the addition of realtime data transmission from the drone, enhanced geographical localization and multimodal sensor information. Full integration with railway maintenance databases and live operational data may enable a more continuous monitoring of the infrastructure and more flexible maintenance planning.

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