Plagiarism Checker X - Report

Originality Assessment

11%

Overall Similarity

Date: Apr 21, 2025 (09:01 AM)
Matches: 1303 / 11792 words
Sources: 64

Remarks: Moderate similarity detected, consider enhancing the document if necessary.

Verify Report:
Scan this QR Code

A Project Report On “Highspeed Railtrack Inspection System” Submitted in partial fulfillment of the requirements For the degree of Bachelor of Engineering by Miss. Ayushi Dinesh Pandey UCN No. MA2113 Mr. Sairaj Mangesh Shinde UCN No. MA2119 Mr. Rohit Dilip Solanki UCN No. MA2120 Supervisor Prof. Chhaya Patil [19] DEPARTMENT OF MECHANICAL ENGINEERING Vishnu Waman Thakur Charitable Trust’s VIVA INSTITUTE OF TECHNOLOGY University of Mumbai (2024 – 2025)

i CERTIFICATE This is to certify that the project entitled “Highspeed Railtrack Inspection System” is a bonafide work of “Ayushi Dinesh Pandey” (UCN No. MA2113), “Sairaj Mangesh Shinde” (UCN No.MA2119), “Rohit Dilip Solanki” (UCN No. MA2120) submitted to the University of Mumbai in partial fulfillment of the requirement for the award of the degree of “Bachelors of Engineering” in “Mechanical Engineering”. Prof. Chhaya Patil Dr. Niyati Raut Supervisor/Guide Faculty Advisor Dr. Niyati Raut Dr. Arun Kumar Head of Department Principal

ii Project Report Approval for B. E. This project report entitled “Highspeed Railtrack Inspection System” by “Ayushi Dinesh Pandey”, “Sairaj Mangesh Shinde”, “Rohit Dilip Solanki” is approved for the degree of “Bachelor of Engineering” in “Mechanical Engineering”.

Examiners 1.__________________________ 2.__________________________

Date: Place: Virar

iii Declaration I declare that this written submission represents my ideas in my own words and where others' ideas or words have been included, I have adequately cited [8] and referenced the original sources. I also declare that I have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in my submission. [3] I understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed. -------------------------------------- (Signature) (Ayushi Dinesh Pandey – MA2113) -------------------------------------- (Signature) (Sairaj Mangesh Shinde – MA2119) -------------------------------------- (Signature) (Rohit Dilip Solanki – MA2120) Date:

iv Abstract The High-Speed Rail Track Inspection System is an advanced solution designed to enhance railway safety by enabling real-time monitoring of track conditions at speeds ranging from 15 km/h to 120 km/h. Unlike conventional track inspection methods that require trains to slow down to 0–15 km/h, this system allows continuous, high-speed assessments without disrupting operations. It utilizes a combination of acoustic and ultrasonic sensors to detect both internal and surface-level rail defects, such as cracks and structural anomalies, which could lead to severe failures if left undetected. The system is mounted directly onto the bogie of a train, eliminating the need for dedicated inspection vehicles and ensuring seamless integration with existing railway infrastructure. Acoustic sensors analyze sound wave propagation within the rails to identify internal defects, while ultrasonic sensors provide a comprehensive surface-level examination. The collected data is processed in real-time using a Arduino D1 Wi-fi, which acts as the system's central processing unit. A key feature of this system is its machine learning-based defect prediction model, which has been trained on historical track failure data. By analyzing sensor inputs, the model can [45] detect early signs of deterioration and predict potential failures, allowing railway operators to implement proactive maintenance strategies. The system is further enhanced by an integrated GPS module, which logs the precise geographic location of identified defects, ensuring that maintenance teams can efficiently locate and address problem areas. The primary benefits of this system include increased inspection speed, [1] real-time fault detection, and predictive maintenance capabilities. By [24] reducing reliance on manual inspections and eliminating the need to slow down trains, this solution enhances operational efficiency while minimizing maintenance costs.

Furthermore, its ability to analyze historical trends enables railway operators to predict defect progression, reducing the likelihood of sudden failures and derailments.

ix Abbreviation RDSO - Research Design and Standards Organization ML - Machine Learning UP - Uttar Pradesh RIC - Rail Inspection Car TRV- Track Recording Vehicle NDT – Non-Destructive Testing DNN - Deep Neural Networks CNN - Convolutional Neural Networks RNN - Recurrent Neural Networks MRSDI-CNN - 43 Multi-Model Rail Surface Defect Detection System SSD - Shot MultiBox Detector YOLOv3 - 57 You Only Look Once version 3 DAS - Distributed Acoustic Sensing WILD - Wheel Impact Load Detectors ITMS - Integrated Track Monitoring System HSRTI - High Speed Rail Track Inspection TP - True Positive TN - True Negative FP - False Positive FN - False Negative MHz - Mega Hertz

Mah – Milliampere-hour

x Organization of Report The dissertation report of research work has been organized as follows: Chapter 1 35 provides an overview of railway track inspection challenges and highlights the need for an advanced High-Speed Rail Track Inspection System. It discusses the motivation behind the research, the objectives of the project, and the scope of the proposed solution. Chapter 2 presents an extensive review of 30 research papers related to railway track inspection technologies. It critically examines existing inspection methods, their limitations, and recent advancements in ultrasonic sensing, machine learning, and IoT-based railway monitoring. Chapter 3 defines 1 the limitations of traditional railway track inspection methods, emphasizing their slow speed (0-15 km/h), manual processes, and lack of real-time predictive capabilities. It highlights how the HSRTI system aims to overcome these challenges by enabling automated fault detection at speeds of 15-120 km/h. Chapter 4 explains the structured approach followed to develop the HSRTI system, covering Research and Planning, Hardware Selection & Fabrication, Software & Machine Learning Model, System Integration & Testing. Chapter 5 presents the experimental results obtained from testing the HSRTI system. It discusses fault detection accuracy (90-95%), real-time data transmission efficiency (2-3 sec delay), and mobile application performance. It also evaluates the system's effectiveness based on field testing at the Virar railway car shed. Chapter 6 summarizes the key findings of the research, emphasizing the system's real-time detection accuracy, mobile app usability, and predictive maintenance capabilities. It also discusses future improvements, including AI-based image processing, edge computing, and large-scale deployment in high-speed rail networks.

1 Chapter 1 Introduction Train derailments are a serious concern for railway networks across the world, particularly in India, where an average of 30 derailments occur each month[1]. These accidents cause substantial loss of life, economic damage, delays, and

disruption in operations. The root causes of derailments include poorly maintained tracks, defects in coaches and wagons, deviations from permissible track parameters, and outdated infrastructure[1]. Despite ongoing modernization efforts, the rate of derailments has been increasing, with a recorded 36 cases in 2022-23, up from 27 in 2021-22.[statista] In response to this persistent issue, there is a clear need for more advanced and efficient track inspection systems to prevent such accidents. Currently, the conventional inspection systems in place operate at slow speeds, typically up to 15 km/h, limiting their coverage and efficiency[21]. This results in missed opportunities for timely identification of track-related issues, leaving sections of railway vulnerable to failures. Currently used track monitoring system is known as ITMS (Integrated Track Monitoring System) which is very costly and is an independent vehicle running on railway tracks of Indian railways at speed of 20km/h to 200km/h in garud inspection models which are prominently used in cities[28]. In remote areas this inspection is carried out manually on small motor operated vehicles on speed range of 0km/h to 15km/h which is very low[14].

2 1.1 Project Background The High-Speed Rail Track Inspection System is a cutting-edge solution designed to enhance the safety and efficiency of railway networks by continuously monitoring track health during train operations at speeds ranging from 15 km/h to 120 km/h. Mounted on the bogie of a moving train, this system utilizes acoustic sensors to detect internal and surface defects such as cracks, misalignments, and structural flaws in real time upto 10cm in depth due to 5MHz ultrasonic sensors[5]. By collecting and processing data through advanced machine learning models, the system not only identifies faults but also predicts potential failures, enabling predictive maintenance and reducing the risk of derailments. Unlike traditional low-speed inspection methods that disrupt train schedules and fail to detect internal flaws, this system operates while the train is in motion, minimizing downtime and ensuring comprehensive track analysis. The adoption of this high-speed inspection technology addresses the growing need for reliable and efficient railway monitoring, ultimately contributing to enhanced operational safety,

reduced accidents, and lower maintenance costs for the railway network. Figure 1.1 Train Derailed in UP [CNN News] Figure 1.2 Derailed Train [ABP News] Figure 1.3 Yearly Derailment Statics [Ministry of Railways]

3 1.1.1 Types of Faults in Railway Tracks 1. Split heads: A split head in a railway track 58 is a type of rail defect where both the head (top surface) and web (middle section) of the rail develop a longitudinal crack. This usually occurs due to repetitive stress, rolling contact fatigue, or manufacturing defects, leading to progressive internal cracking[8]. Over time, the crack widens, compromising the rail's structural integrity. If undetected, it can result in rail breakage, leading to derailments or severe operational disruptions. Split heads also impact train stability, ride comfort, and track maintenance costs, making regular inspection and predictive maintenance crucial to prevent failures. High-speed trains and heavy freight loads exacerbate this issue, making early detection through ultrasonic testing or AI-based monitoring essential for railway safety. 2. Gap in Two Consecutive Railway Tracks: Figure 1.4 Split Heads [Ministry of Railways] Figure 1.5 Gap in Tracks [GPS Camera-Virar carshed]

4 A joint gap defect occurs when there is excessive spacing between two rail sections, often due to temperature variations, improper track laying, or mechanical wear at the joints[8]. In cold weather, rail contraction increases the gap, while in hot weather, excessive expansion can cause buckling. These gaps lead to impact forces as train wheels pass over them, causing discomfort to passengers, accelerated wear on wheels and rails, and potential derailments. Frequent maintenance 20 is required to ensure the gaps are within safe limits to prevent structural failure. 3. Faulty Welds: Faulty welds occur due to improper welding techniques, material inconsistencies, or insufficient cooling time after welding. This defect weakens the rail at the welded joint, making it prone to cracking and breakage under repeated train loads[1][8][12]. Over time, the weakened section can completely fail, causing derailments or track misalignment. Poorly welded joints also lead

to rough rides, increasing maintenance costs and the risk of early rail replacement. Regular ultrasonic inspections are essential to detect weak welds before they become hazardous. 4. Internal Faults in Weld: Internal weld faults such as porosity, inclusions, or microscopic cracks form during the welding process due to impurities, incorrect temperature control, or inadequate fusion of the welded sections[4]. These defects are not always visible but significantly weaken the rail structure. Under repeated stress, the internal cracks can grow, leading to sudden rail fractures, posing a serious risk to train operations. Undetected weld faults can lead to derailments or catastrophic track failures, making advanced inspection methods like radiographic or ultrasonic testing critical for safety. 5. Misaligned Profile: Figure 1.6 Misaligned Profile [GPS Camera-Virar carshed]

5 A misaligned rail profile occurs when the track is not properly laid, ground movement shifts the rails, or fastening components loosen over time. This misalignment results in uneven force distribution on the rails and train wheels, leading to excessive vibrations and increased wear on rolling stock. Misaligned tracks can cause wheel slipping, inefficient fuel consumption, and derailments, especially at high speeds. To prevent such issues, regular track realignment and laser-based inspections are necessary to maintain smooth railway operations[24]. 6. Irregular Rail Wear: Faulty rail profiles occur when the rail head wears unevenly due to improper grinding, unbalanced train loads, or frequent braking in specific sections[12]. This defect alters the wheelrail interaction, leading to excessive vibration, increased rolling resistance, and premature component wear. Faulty profiles can also cause poor ride quality, higher energy consumption, and increased maintenance needs. Rail grinding and periodic track monitoring help restore the rail shape and extend track lifespan. 7. Squats: Figure 1.7 Irregular rail wear [GPS Camera-Virar carshed] Figure 1.8 Squats [Ministry of Railways]

6 Squats are localized depressions or cracks in the rail surface caused by high-impact loads from heavy trains or defective wheels. These defects create sudden shock loads,

leading to vibration, instability, and faster deterioration of the rail track. Squats can propagate into deep fractures, 36 making them a significant safety concern. Predictive maintenance, including track lubrication and AI-based monitoring, can help detect and prevent squats before they become hazardous[12]. 8. Broken Rails: A broken rail is a severe defect where the rail completely fractures due to fatigue, thermal expansion, or excessive loading. This 35 is one of the most dangerous railway defects, as it can cause train derailments, major accidents, and service disruptions. Broken rails are often a result of undetected cracks that grow over time. Regular ultrasonic inspections, advanced AI monitoring, and temperature-based rail expansion control are essential measures to prevent such failures. Chapter Summary This chapter introduces the project along with the past data of railway accidents. The chapter also summaries various faults found in railway tracks, the reasons behind those faults and the effect it has on working of railways.

7 Chapter 2 Literature Review 2.1 Review G. Vijayalakshmi, J. Gayathri, K. K. Senthilkumar, G. Kalanandhini et. al., (2022) [1] Recent developments in automated rail inspection systems have significantly improved railway safety by addressing track faults 25 that can lead to derailments. Traditional manual inspections are prone to errors, but intelligent systems using image analytics, sensors, and multi-source data provide real-time, accurate assessments of critical rail components like tie plates and nuts. These systems reduce human involvement and ensure track health, especially by detecting issues like elastic rail clip breaks. Field tests confirm that automated inspections can enhance railway safety by minimizing accidents and improving reliability. 23 G. Jing, X. Qin, H. Wang, and C. Deng (2022) [2] Railway infrastructure is vital to modern society, supporting daily transport of passengers and goods. Traditionally, railway inspections have been 39 conducted by human inspectors or manually operated machines like track recording vehicles (TRVs). However, these methods are 49 labor-intensive, time-consuming, and prone to subjectivity, particularly when performed under poor conditions. While TRVs use NonDestructive Testing (NDT) techniques for more standardized inspections, the high

costs and

8 low inspection frequency, combined with reliance on analysts' experience, limit their efficiency. Recent demands for better railway safety and increased mileage, along with the need to reduce emissions, have sparked interest in railway inspection robots. These robots, equipped with advanced sensors and data-processing capabilities, offer potential solutions to challenges posed by manual inspections by automating fault detection in hazardous environments. While some rail companies, like Canadian National Railway, have introduced automated systems, railway inspection robots are not yet widely adopted. This paper reviews the development, 23 challenges, and future prospects of railway inspection robots. L. Kou, M. Sysyn, S. Fischer, J. Liu, and O. Nabochenko (2022) [3] Detecting rail surface damage is crucial for railway safety, especially in identifying cracks that lead to defects and shorten the rail's lifespan. Traditional methods like magnetic particle inspection are accurate but expensive, slow, and impractical 1 due to the complexity and equipment involved. Recent advancements have shifted towards using deep learning and semantic segmentation for crack detection. This method, relying on data collected from rail surfaces and neural networks, offers a faster, more cost-effective alternative by using simple cameras instead of complex machinery. Studies show that this approach maintains high accuracy, and when combined with highfrequency cameras, it further enhances detection speed. This technique is efficient, economical, and environmentally friendly, making it a promising solution for future rail damage detection. J. Sresakoolchai and S. Kaewunruen (2021) [4] Machine learning, particularly 1 deep learning, has emerged as a promising technique for detecting railway defects. This study explores the application 50 of deep learning models, including deep neural networks (DNN), convolutional neural networks (CNN), and recurrent neural networks (RNN), to detect and evaluate the severity of combined rail defects like settlement and dipped joints. Using simulated axle box accelerations from the D-Track simulation, both simplified and raw data were applied to develop these models. The CNN model demonstrated excellent

performance, achieving 99% accuracy in detecting combined defects and was also effective in assessing dipped joint severity. Meanwhile, the RNN model was most accurate in evaluating settlement severity. Overall, deep learning techniques prove to be highly effective in accurately identifying and categorizing railway defects, offering significant potential for enhancing rail safety and maintenance. Hui Zhang; Yanan Song; Yurong Chen et. al., (2021) [5] Rail surface defects pose significant challenges to the safety and efficiency of train operations, necessitating quick and accurate detection. While many solutions have been proposed, current methods often lack in

9 speed, accuracy, and comprehensiveness. This study introduces a multi-model rail surface defect detection system (MRSDI-CNN) utilizing deep learning techniques, specifically the improved Single Shot MultiBox Detector (SSD) and You Only Look Once version 3 (YOLOv3), both one-stage networks. By enhancing the detection capabilities of these convolutional neural networks for various defect sizes, the system can accurately identify 7 different types of rail squats without compromising detection speed. The experimental results demonstrate that this method outperforms previous approaches in both accuracy and efficiency, making it a promising solution for real-time rail surface defect detection. Hongfei Yang; Yanzhang Wang; Jiyong Hu et. al., (2021) [6] 7 Timely detection of rail surface defects is crucial for preventing rail failures and ensuring railway safety. However, existing methods struggle with performance when rails are contaminated with rust or oil. This study introduces 51 a multilevel, end-to-end rail surface defect detection method that improves both speed and accuracy. The method begins with rail extraction using the stability of edge pixel standard deviations, followed by defect segmentation using a combination of the differential box-counting (DBC) method and GrabCut algorithm. YOLO v2 is then applied to accurately locate and detect defects. Experimental results show 7 a high accuracy of 97.11% and strong robustness across various scenarios, making this method highly effective for real-time rail defect detection. 5 F. Guo, Y. Qian, D. Rizos, Z. Suo, and X. Chen (2021) [7] Rail surface defects significantly impact riding comfort and

track safety, with a notable contribution to derailments, as reported by the Federal Railroad Administration (FRA). While many detection methods have been developed, traditional approaches remain labor-intensive, time-consuming, and dependent on specialized equipment. 17 To address these limitations, this study introduces a cost-effective, computer vision-based instance segmentation framework using Mask R-CNN for automatic rail surface defect inspection. A custom 44 rail surface defect dataset was built, and the model was retrained and fine-tuned for improved accuracy. Results show that the ResNet101 backbone, with a learning rate of 0.005, achieved optimal performance, indicating promising potential for realworld applications in rail maintenance. Jianwei Liu; Hongli Liu; Chinmay Chakraborty et. al., (2021) [8] The periodic monitoring and inspection of rail fasteners are crucial for maintaining railway safety, given their vulnerability to damage. Recent advancements in 1 Industrial Internet of Things (IIoT) and artificial intelligence (AI) have facilitated online inspection of fastener faults through IoT

vehicles equipped with various sensors and cameras. However, challenges remain, particularly in gathering sufficient samples of faulty fasteners for effective training of AI models. This study proposes a cascade learning embedded vision inspection method utilizing deep convolutional neural networks (DCNN) for rail fastener inspection. The methodology involves two steps: first, 2 using a modified single shot multibox detector (SSD) to identify fastener regions in railway images, followed by a key component detection (KCD) method based on an enhanced faster region convolutional neural network (RCNN) for fault detection. Experimental results demonstrate the proposed method's efficacy, achieving 2 an average precision of 95.38% and an average recall of 98.62% in fastener detection, significantly outperforming traditional manual inspection methods. Y. Sun et. al., (2021) [9] Rail corrugation is a prevalent periodic wear pattern on railway tracks 25 that can lead to increased noise and vibrations, adversely affecting surrounding environments. Traditional rail corrugation inspection methods rely on offline inspection trolleys, while online monitoring solutions are often dependent on external batteries, requiring significant manual upkeep. This study introduces an innovative online rail corrugation monitoring system that utilizes a self-contained energy harvesting mechanism, featuring an improved triple-magnet configuration for enhanced performance. The research explores the 11 differences between repellent and attractive magnetic configurations and employs comprehensive broadband sinusoidal sweeping and stochastic vibration tests to assess railway track spectra. By leveraging wavelet theory for time–frequency analysis, the system effectively identifies rail corrugation defects through the induced voltage generated by the energy harvesters. The findings demonstrate that this sustainable approach can collect rail vibration energy across a broader frequency spectrum, thereby minimizing reliance on environmentally harmful batteries and 20 reducing the need for manual intervention in railway track inspections. Sayed Mohammad Mousavi Gazafrudi; Davood Younesian; Mehran Torabi et. al., (2020) [10] Frequent inspection of railway tracks is crucial for reducing noise and vibration during operation, with rail corrugation measurement being a primary focus. Rail corrugation, a result of wear during operation, generates dynamic vertical wheel-rail contact forces that contribute significantly to vibrations. Additionally, the interaction between corrugation wavelength and railway vehicle speed creates dynamic excitations, leading to increased noise levels. Traditional measurement systems, which rely on acceleration or chord measurements, are often unreliable due to their dependence on physical contact or specific track characteristics. 17 To address these limitations, this article presents a novel measurement system utilizing image processing based

11 on the laser triangulation principle for precise and rapid rail corrugation assessment. The proposed system demonstrates high-speed and accurate measurement capabilities, as evidenced by experimental results, making it a promising solution for practical applications in rail corrugation monitoring. S. Wang, F. Liu, and B. Liu (2020) [11] Ballastless track systems are prone to various common diseases, including crevice, beam crevice, cracking, and empty spaces, primarily resulting from thermal expansion and

contraction of track slabs influenced by temperature and humidity changes. The timely inspection of these tracks is crucial for ensuring railway safety, yet current methods rely heavily on nighttime inspections and lengthy maintenance cycles, which are laborintensive and prone to oversight. Traditional inspection techniques, such as acceleration measurement and image processing, have limitations in real-time monitoring and applicability over long distances. Consequently, there has been a growing interest in optical fiber sensing technologies, particularly Fiber Bragg Grating (FBG) and Distributed Acoustic Sensing (DAS), which have shown promise for real-time monitoring of strain, temperature, and rail conditions. DAS, in particular, offers advantages in cost-effectiveness, long-distance monitoring, and strong anti-interference capabilities. However, challenges remain, including installation difficulties and system integration issues. This study proposes a novel rail track inspection scheme utilizing DAS technology, enhanced by a deep convolutional network, to address these challenges and improve monitoring capabilities for small events and defects. The proposed method demonstrates improved performance over traditional inspection techniques, highlighting its potential for practical application in railway maintenance. F. Guo, Y. Qian, and Y. Shi (2020) [12] The Federal Railroad Administration (FRA) mandates regular track inspections to prevent accidents caused by inadequate maintenance, but daily inspections across the extensive U.S. rail network are impractical. Historically reliant on personnel, inspections have progressed to automated methods like laser measurements, groundpenetrating radar, and ultrasonic techniques to enhance safety and efficiency. Despite improvements, these technologies often come with high costs and operational complexity, particularly amid rising transportation demands and limited inspection windows. Previous automation efforts have focused on specific track components but often require substantial computational resources. Recent advances in deep learning, especially convolutional neural networks (CNNs), offer promising solutions, yet few studies have applied these methods in railroad engineering. This study proposes an improved YOLOv4 object detection framework

12 aimed at delivering a fast, accurate, and cost-effective inspection system for railroad track components, addressing the critical need for enhanced safety measures in rail transport. 5 F. Guo, Y. Qian, Y. Wu, Z. Leng, and H. Yu (2020) [13] In the U.S., the Federal Railroad Administration (FRA) requires regular railroad track inspections to ensure safety and efficiency. However, traditional manual inspections are inefficient and subjective, often failing to accurately detect missing or damaged components like spikes and clips. 6 Advanced technologies such as ground-penetrating radar and LiDAR are expensive and require specialized training. This study introduces 46 a real-time pixel-level detection framework for rail component inspection, leveraging the first public image database for rails, spikes, and clips. The improved instance segmentation models achieve a 24 mean average precision (mAP) of 59.9 for bounding boxes and 63.6 for masks, while processing over 30 frames per second on highresolution video. This automated approach significantly enhances 1 the accuracy and efficiency of track inspections, addressing crucial safety issues in the industry. C. Yang, Y. Sun, C. Ladubec, and Y. Liu (2020) [14] The railway industry allocates nearly 40% of its revenue to maintaining and upgrading infrastructure, highlighting the critical need for advanced maintenance strategies to enhance safety and reduce costs. Recent trends emphasize condition monitoring 38 and the integration of artificial intelligence (AI) technologies to improve fleet reliability and enable predictive maintenance, which can significantly decrease failures and unplanned maintenance. Wheel failures and broken rails are primary 25 causes of train derailments, with wheel-related issues alone contributing to half of all incidents, incurring significant costs for the North American rail sector. To combat these issues, techniques such as Wheel Impact Load Detectors (WILD) have been implemented to monitor wheel performance in real-time, and predictive models have been developed to foresee wheel failures. Various methods, including accelerometer-based 7 detection of rail surface defects, have emerged to identify rail issues, but these often require additional visual inspections due to limitations in distinguishing between different types of defects. Recent advancements in deep learning, particularly convolutional neural networks (CNNs), offer

promising solutions by enabling endto-end classification of raw acceleration data, potentially streamlining rail joint detection without extensive preprocessing or the need for separate models for each track side. This literature underscores the need for continued innovation in detection technologies to improve railway 14 safety and operational efficiency.

13 J. Jang, M. Shin, S. Lim, J. Park, J. Kim, and J. Paik (2019) [15] Image-based railway inspection systems (IRIS) leverage 10 image processing and computer vision algorithms to enhance safety and maintenance by automatically detecting defects in railways from RGB or gray-scale images. Traditional inspection methods have relied heavily on simple image processing techniques, including feature extraction and histogram analysis, yet these approaches 1 are limited by the extensive inspection regions typical in railway environments. Various studies have addressed these challenges; for instance, Min et al. developed a defect detection system using hue channel analysis, while Karakose et al. utilized Canny edge detection for fault diagnosis. 33 Recent advancements have seen the incorporation of deep learning to improve accuracy in defect detection, with works by James et al. and Gibert et al. employing deep neural networks for segmentation and multi-task learning, respectively. Additionally, railroad inspection cars (RICs) have been deployed for comprehensive facility inspections but are constrained by the two-dimensional imaging methods employed during movement. The proposed novel inspection system enhances this process by utilizing 10 a gray-scale line scan camera to obtain high-resolution images and employing deep learning for effective object detection, thereby offering a more efficient solution for maintaining urban railroad infrastructure, especially in subway tunnels. This review highlights the transition from conventional methods to sophisticated, automated systems that can significantly improve the efficiency and accuracy of railway inspections. 15 Xiating Jin; Yaonan Wang; Hui Zhang et. al., (2019) [16] The rail inspection system (RIS) has emerged as a vital technology for monitoring the structural integrity of steel rails by detecting surface defects. Traditional inspection

methods often prove costly and error-prone, necessitating advancements in detection techniques and interpretation. In response to these challenges, the proposed [15] deep multimodel RIS (DM-RIS) integrates a spatially constrained Gaussian mixture model for effective defect segmentation alongside Faster R-CNN for object localization. By incorporating spatial information through an improved [56] Gaussian mixture model based on Markov random fields (MRF), the system enhances edge segmentation accuracy and speed. Additionally, the DM-RIS is fortified against environmental variations by training on a diverse set of labeled samples with challenging conditions, such as weak illumination and noise. [1] Experimental results indicate that the DM-RIS achieves impressive performance metrics, with 96.74% precision, 94.13% recall, and a processing speed of 0.485 seconds per frame. This positions the DM-RIS as a robust alternative to established inspection techniques, highlighting its potential for advancing the efficiency and reliability of railway maintenance.

14 Junbo Liu; Yaping Huang; Qi Zou et. al., (2019) [17] [12] Vision-based automatic railway fastener inspection poses significant challenges, primarily due to the reliance on manual operations and the limitations of existing supervised learning methods. [26] The high cost of training labels and the prevalence of imbalanced datasets hinder the performance of fastener inspection systems. To address these issues, [12] a novel vision-based fastener inspection system (VFIS) has been proposed, leveraging principles from few-shot learning. This system utilizes an online template matching-based classification method to autonomously collect and annotate a substantial number of fastener samples with minimal annotated templates required. Additionally, a similarity-based deep network is employed to effectively manage imbalanced datasets. Extensive experiments on a large-scale fastener dataset demonstrate the VFIS's efficacy, achieving a remarkable 99.36% detection rate [12] for fastener localization and a 92.69% accuracy for fastener classification. Notably, the VFIS excels in identifying defective fasteners, with [2] an average precision of 92.63% and recall of 92.88%. These results indicate that the VFIS presents a promising advancement

in the automation of railway fastener inspection, potentially improving operational efficiency and safety. A. Sánchez-Rodríguez, M. Soilán, M. Cabaleiro, and P. Arias (2019) [18] The increasing demand for digital models of real-life scenarios, particularly in the railway sector, has spurred significant research into the use of laser scanning systems for infrastructure inspection and maintenance. Traditional methods of inspecting railway track irregularities and catenary systems have evolved, with mobile laser scanning (MLS) becoming a preferred approach due to its safety and efficiency in data collection. Previous works have explored various techniques for classifying and inspecting point clouds obtained from laser scanning, with Che et al. providing an overview of recent advancements in object recognition and classification for LiDAR data. Techniques have included heuristic methods and algorithms that leverage spatial relationships among LiDAR data points to classify railway objects, such as tracks and overhead power lines. Notably, Arastounia has developed algorithms for automatic classification of railway power lines using both terrestrial and aerial laser scanning data, while Pastucha and Zhang have enhanced power line detection using trajectory data and region growing algorithms. Recent trends indicate a shift towards deep learning methodologies for point cloud classification, as seen in the works of Luo et al. and Sánchez-Rodríguez et al., who employed advanced classifiers like Conditional Random Fields and Support Vector Machines. Despite these developments, there remains a need for fully automated methods capable of accurately measuring power line gauges and catenary deflections without human intervention. This paper

15 addresses this gap by presenting a novel approach to automatically classify and inspect LiDAR point clouds of aerial contact line systems in railway tunnels. Ashish James; Wang Jie; Yang Xulei; Ye Chenghao; Nguyen Bao Ngan et. al., (2018) [19] The reliable and cost-effective inspection of rail tracks is crucial for maintaining the safety and efficiency of railway operations. In recent years, automated vision-based track inspection methods that leverage computer vision and pattern recognition have emerged as promising solutions for detecting surface defects. These techniques are favored for their low cost,

high speed, and strong performance in defect identification. However, the challenge of varying failure modes and the extensive range of image variations can lead to false alarms, complicating the inspection process. To address these challenges, recent studies have proposed multiphase deep learning techniques that enhance detection accuracy. For instance, initial segmentation of images allows for the isolation of regions of interest, which are then cropped and processed by binary classifiers to distinguish true defects from false alarms. This approach has shown to significantly improve detection performance by effectively reducing the false alarm rate, thus making automated vision-based inspections a more viable alternative for rail track maintenance. J. Ye, E. Stewart, and C. Roberts (2018) [20] The safety and reliability of railway systems are increasingly jeopardized by rail defects, exacerbated by rising train speeds, axle loads, and traffic density. Reports from the European Railway Safety Agency highlighted alarming statistics, with a derailment or collision occurring every other day in the EU between 2010 and 2011, primarily due to track defects. As the UK's rail network continues to expand, efficient inspection methods have become a critical concern for the industry. Over the past few decades, non-contact inspection techniques such as ultrasound, eddy currents, and lasers have gained prominence, with laser-based methods emerging as the most effective for detecting surface defects. Comprehensive surveys, such as the one conducted by Papaelias et al., affirm the applicability of laser technology in rail inspection. Laser-based systems, including Network Rail's New Measurement Train and MERMEC's measurement technologies, provide highresolution, non-contact assessments of rail conditions while enabling inspections at train speeds. However, conventional 2D imaging techniques can struggle with longitudinal defects, such as cracks and deformations. Recent advancements in 3D imaging technology offer promising enhancements in defect detection, allowing for a more comprehensive analysis of rail surfaces. This paper proposes a laser-based system that integrates 3D techniques, aiming to improve the detection and characterization of various longitudinal surface defects beyond the capabilities of

16 traditional 2D methods, thereby enhancing maintenance strategies and prolonging component lifespans. S. Singh (2018) [21] Railroad track inspection systems have evolved to incorporate advanced technologies that enhance the accuracy and efficiency of track monitoring. A notable innovation involves the integration of multiple track scanning sensors, a data storage unit, and a scan data processor, which collectively enable automatic analysis of track scan data. This system is designed to detect various track components from a predetermined list by analyzing features identified within the scan data. The sensors, data storage, and processing units are mounted on a common support structure that can be affixed to railway vehicles, allowing for seamless integration into existing passenger and freight trains. To address the challenges posed by dynamic forces during operation, the system employs inertia sensors and a common master clock, enabling real-time corrections to sensor outputs. This technology supports unattended operation, facilitating continuous monitoring without the need for manual intervention. Additionally, the system's ability to log the locations of track components and defects plays a critical role in proactive maintenance strategies, contributing to improved safety and reliability within the railway infrastructure. Mehran Torabi; S. G. Mohammad Mousavi et. al., (2018) [22] Ensuring the operational safety of railway vehicles, including subways, trams, and various types of trains, necessitates frequent inspections, with a critical focus on wheel diameter and overall geometry. Wheel diameter typically decreases over time due to wear, and deviations between the diameters of wheels on a bogie frame or car body must adhere to strict railway technical standards to avoid derailment risks. Traditional measurement systems often rely on mechanical devices that can be both unreliable and costly due to the need for precise physical contact and high-quality mechanical components. To address these limitations, a novel measurement system leveraging image processing techniques has been proposed. This system modifies the conventional threepoint radius measurement approach, enhancing the efficiency of wheel diameter measurement by streamlining the calculation process. By utilizing advanced image processing, the system minimizes the steps involved in conventional measurements,

resulting in faster operation without compromising accuracy. Experimental results demonstrate the system's capability for industrial application, indicating its potential to significantly improve the reliability and efficiency of wheel diameter inspections in the railway industry.

17 S. Kaewunruen and C. Chiengson (2018) [23] The operation of service train axles over open plain tracks results in significant dynamic loading conditions, which vary based on wheel and rail maintenance levels. The interactions between wheel and rail can lead to high-intensity dynamic loading, particularly in the presence of irregularities in the rail track. These imperfections can lead to the exceedance of permissible stress levels in track components, subsequently accelerating the deterioration of the track, causing issues such as cracking in sleepers and failure of the track substructure. Traditionally, railway track irregularities have been classified into short wavelength (high frequency) and long wavelength (low frequency) defects, with previous studies focusing on each type in isolation. This paper pioneers the exploration of how the coupling of these wavelengths—specifically between dipped rail joints and differential track settlements—affects railway track inspection and maintenance priorities. Using a dynamic multi-body simulation approach, the study evaluates the P1 and P2 forces at the site of track irregularity, alongside rail/sleeper contact forces, ballast pressure, and bending moments in sleepers. The findings indicate that certain patterns of coupled irregularities can significantly reduce dynamic impact factors, while others may lead to increased wheel/rail impact forces. This insight is essential for establishing track performance indicators that can inform and prioritize track inspection and maintenance strategies, ultimately enhancing railway safety and operational efficiency. L. Zhuang, L. Wang, Z. Zhang, and K. L. Tsui (2018) [24] This paper presents a doublelayer data-driven framework aimed at automating the vision inspection of rail surface cracks. The framework first identifies crack locations from rail images and subsequently delineates their boundaries through a method known as feature-based linear iterative crack aggregation (FLICA).

To enhance crack detection, extended Haar-like features are employed to extract significant characteristics from the images. The system utilizes a cascading classifier ensemble, which integrates three single cascading classifiers governed by a major voting scheme to ascertain 4 the presence of cracks. Each classifier comprises a sequence of stage classifiers trained using the LogitBoost algorithm. A scalable sliding window method is implemented to scan rail track images, which are identified using Otsu's method for crack detection. Upon the initial crack registration, FLICA is utilized to accurately discover the crack boundaries. 38 The effectiveness of this data-driven framework is validated with rail images from the China Railway Corporation and Hong Kong Mass Transit Railway (MRT). To benchmark its performance, six existing methods—Otsu's method, mean shift, visual detection systems, geometrical approaches, fully convolutional networks, and U-Net—are employed for

18 comparative analysis. 11 Results indicate that the proposed framework outperforms these established techniques in detecting rail surface cracks, underscoring its potential for enhancing railway safety and maintenance efficiency. G. Gabara and P. Sawicki (2018) [25] This paper explores the application of non-invasive 3D measurement techniques in the railway sector, focusing on 26 both active and passive measurement methods, primarily utilizing mobile systems based on terrestrial laser scanning (TLS) complemented by digital imaging. Mobile LiDAR serves as a fundamental data source for various railway applications, including automated rail modeling, infrastructure recognition, centerline extraction, and clearance gauge measurements. Vision-based methods leveraging digital sensors have been employed 3 for tasks such as rail surface defect detection, clearance obstacle measurement, continuous monitoring of track conditions, and automated visual inspections. The photogrammetric reconstruction of 3D objects is increasingly reliant on dense image matching techniques, particularly the Structure from Motion (SfM) method, which facilitates the generation of dense point clouds. These point clouds enable detailed geometric and semantic analysis of objects. The paper highlights the critical research

problem of assessing the accuracy of point clouds derived from dense image matching for 3D surface reconstruction in close-range applications, building on previous work. [7] The authors propose a novel approach that utilizes image-based point clouds and mesh models for precise 3D reconstruction and measurement of railway tracks, achieving high accuracy (with errors under 1 mm). They argue that, [1] to their knowledge, no existing mobile vision systems utilize solely image-based point clouds for railway applications to achieve such levels of precision, underscoring the potential for innovation in railway inspection and maintenance practices. Jinrui Gan; Jianzhu Wang; Haomin Yu et. al., (2018) [26] Rail surface inspection plays [20] a critical role in the maintenance of railway systems, yet the accurate and efficient identification of potential defects poses significant challenges. This paper introduces [27] a Background-Oriented Defect Inspector (BODI) designed to enhance defect detection by incorporating specific characteristics of the rail track during the inspection process. By reformulating the inspection task to focus on background modeling, BODI utilizes a random sampling stage to create a compact representation of the background without requiring prior information. This approach generates diverse background statistics through sufficient random selections, allowing for effective defect determination by evaluating whether a given pixel belongs to the background. Furthermore, the incorporation of a background update mechanism and parallel processing ensures the system's real-time applicability. The effectiveness of BODI is validated through

19 experiments conducted on a working railway line, with results indicating [1] superior performance compared to existing state-of-the-art methods. This innovative approach offers a promising solution to the challenges faced in rail surface inspection, paving the way for improved railway maintenance and safety practices. A. G. Antipov and A. A. Markov (2018) [27] [53] The Magnetic Flux Leakage (MFL) method is a prevalent non-destructive testing technique utilized for assessing the integrity of ferromagnetic objects, particularly in railway applications. This technique involves magnetizing the test object using a U-shaped magnet, enabling [4] the detection of internal flaws through magnetic

field distortions. MFL has been effectively implemented in various domains, including the inspection of reservoirs, piping, and steel ropes. Within the railway sector, the method is integrated into inspection vehicles to evaluate rail track conditions, often in conjunction with other 61 non-destructive testing methods such as ultrasonic and eddy-current techniques. Despite its advantages, MFL's efficacy is limited by factors such as eddy currents induced by changing magnetic fields, which hinder the detection of deep subsurface defects. Recent advancements have introduced magnetizing systems with increased pole distances, improving 20 the ability to detect rail defects while minimizing the negative effects of eddy currents. Laboratory studies have shown that MFL can maintain efficiency at inspection speeds of 62 up to 200 km/h; however, the focus has primarily been on surface damage, overlooking the critical need for identifying deeper rail head defects. This paper presents a comprehensive investigation into the relationship between MFL data and inspection speed through both 3D computer simulations of dynamic magnetization and field experiments, revealing consistent results and advancing the understanding of MFL's capabilities in real-world rail 5 defect detection. Y. Wu, Y. Qin, Z. Wang, and L. Jia (2018) [28] Rail surface defects pose significant risks to railway safety, making effective detection methods crucial. Traditional inspection techniques, such as manual and rail vehicle inspections, have inherent limitations, including low efficiency and high operational costs. To address these challenges, recent advancements have explored the use of unmanned aerial vehicles (UAVs) for visual inspection of rail surfaces. This paper introduces a novel approach that leverages UAV imagery, focusing on two critical aspects: image enhancement and defect segmentation. A new image enhancement algorithm, 18 Local Weber-like Contrast (LWLC), is proposed to improve the visibility of rail defects under varying sunlight conditions by effectively highlighting and homogenizing the rail surfaces. Additionally, the paper presents a gray stretch maximum entropy (GSME) threshold

20 segmentation method that optimizes defect detection through enhanced gray stretch and noise reduction in UAV-based rail images. Experimental results demonstrate that the

combined LWLC-GSME model achieves impressive recall rates of 93.75% for T-I defects and 94.26% for T-II defects, indicating its effectiveness and practicality for detecting rail surface defects. This UAV-based visual inspection method represents a significant advancement in railway maintenance technology, providing a more efficient alternative to traditional inspection practices. Junping Zhong; Zhigang Liu; Zhiwei Han; Ye Han; Wenxuan Zhang wt. al., (2018) [29] Split pins (SPs) are critical components in ensuring the structural stability of catenary support devices (CSDs) in high-speed railways. The integrity of these pins is vital, as loose or missing defects can compromise the overall safety and functionality of the railway infrastructure. Recent advancements in automated inspection systems have led to the development of a three-stage defect inspection method specifically for SPs, utilizing an enhanced deep convolutional neural network (CNN) known as PVANET++. This approach begins with the localization of SPs through the PVANET++ framework, which employs the Hough transform and Chan-Vese model for precise identification. The system then applies three proposed criteria for effective defect detection. A novel anchor mechanism within PVANET++ facilitates the generation of suitable candidate boxes for the SPs, while the integration of multiple hidden layer features enhances the model's ability to construct discriminative hyperfeatures. Comparative evaluations of PVANET++ against several leading deep CNN architectures reveal its superior accuracy and considerable speed, highlighting its potential as a reliable solution for the automated inspection of SP defects. This innovative inspection system addresses the critical need for reliable monitoring in railway safety, emphasizing the importance of adopting advanced machine learning techniques in infrastructure maintenance. Q. Mao, H. Cui, Q. Hu, and X. Ren (2018) [30] The rapid expansion of high-speed railways in China, which surpassed 20,000 km by 2015, underscores the critical need for reliable fastener systems that maintain track integrity at speeds of 300–350 km/h. Fasteners serve essential roles in connecting rail tracks and pads, reducing vibrations, and minimizing operational noise. Failures in fasteners, such as loosening or absence, pose significant safety risks, necessitating periodic inspections by railway authorities. Traditional manual inspection methods are laborintensive, slow, and hazardous, highlighting 1 the urgent need for automated solutions. Recent advancements have focused on developing two-dimensional vision systems, with notable contributions from researchers employing various techniques, including wavelet transforms and

21 pattern recognition algorithms 2 for real-time detection of fastener defects. While initial methods could only ascertain 33 the presence or absence of fasteners, newer approaches successfully identify partially worn fasteners. Moreover, the introduction 54 of structured light sensors has enhanced inspection capabilities, providing high precision in three-dimensional measurements. However, many structured light systems primarily detect missing fasteners without addressing looseness. This study advances the field by leveraging commercial structured light sensors to generate dense 3D point clouds and employing decision tree classifiers to identify not only missing but also partly worn or skewed fasteners. The methodology incorporates innovative techniques for segmenting key components and evaluating fastener looseness, demonstrating significant potential for improving safety and maintenance efficiency in high-speed railway systems. Chapter Summary This chapter shows literature review of various journal papers related to railway track inspection system in total thirty research paper are studied to and various conclusions are drawn from them.

22 Chapter 3 Problem Definition 3.1 Problem Statement Traditional railway track inspection systems have several limitations, most notably their speed and the manual processes involved in detecting faults. These systems can inspect tracks only at low speeds (0-15 km/h)[21], leading to significant delays in operations and creating inefficiencies in 4 the detection of internal faults, misalignments, and wear on the tracks. Moreover, the absence of real-time predictive capabilities further exacerbates the issue, as maintenance is often reactive rather than preventive. In this context, this project seeks to develop a High-Speed Rail Track Inspection System, installed on the bogie of railway

trains, that can perform real-time 4 detection of internal and surface defects on railway tracks. The system will use acoustic sensors and advanced 1 machine learning models to analyse the data gathered, predict potential failures, and improve maintenance schedules. This system will be capable of operating at speeds between 15 km/h and 120 km/h, addressing the limitations of conventional systems, and improving railway safety and efficiency.

23 3.2 Objectives • To develop a track inspection system which can work on higher speeds. • To perform predictive maintenance on rail tracks utilizing 17 machine learning models and acoustic sensors. • To develop a system which can continuously perform inspections without disrupting the railway schedules. • To predict the track health and perform maintenance before failure occurs. • To collect real-time data and use it for analysis. • To minimize accidents due to negligence of track maintenance. • To provide a dedicated application where the railway authorities will receive the precise location to perform maintenance. Chapter Summary This chapter discusses the problems related to existing railway track monitoring system used in Indian railways criticizing its slow speed and how the proposed project can help solve the problems currently faced in railway track inspection.

24 Chapter 4 Methodology To gain knowledge on existing technologies on rail track inspection we studied the rail track inspection systems currently used by Indian Railways which are developed and managed by RDSO. Currently the monitoring system sends the alert once broken track is identified. The major areas where the track breaks are at welds.[1] The development of the rail track inspection system followed a systematic and structured approach to ensure the accuracy and reliability 1 of the fault detection process. The methodology 4 can be divided into several key phases, including research and planning, hardware selection and procurement, hardware fabrication and assembly, software development, data collection, machine learning model development, and system

integration and testing. The project began with extensive research on existing railway track inspection methods, focusing on both traditional and automated approaches. Several research papers were reviewed to understand the effectiveness of ultrasonic sensors in detecting track faults and the feasibility of integrating machine learning for predictive maintenance[16]. The study also helped identify the types of railway track faults that needed to be detected, including cracks, misalignments, and surface deformations. This phase also involved defining the scope, selecting the appropriate hardware and software tools, and formulating an initial design for the system. Based on the research findings, the required hardware components were identified and procured. The key components included ultrasonic sensors for distance

25 measurement, a microcontroller (Arduino-based ESP8266) for data acquisition and transmission, and necessary communication modules for wireless data transfer. Other supporting components such as power supply units, connectors, and mounting hardware were also acquired. Special attention was given to the selection of sensors capable of operating efficiently at high speeds ranging from 15 km/h to 120 km/h, ensuring reliable data collection during real-time railway inspections. To house the sensors and microcontroller securely, 3Dprinted casings and mounting brackets were designed and fabricated. These casings ensured the durability and stability of the sensors, protecting them from external environmental factors such as vibrations, dust, and weather conditions. The sensors were strategically positioned to cover critical areas of the railway track and detect faults accurately. Once the fabrication was complete, the hardware components were carefully assembled, and all electrical connections were established. Parallel to hardware assembly, a mobile application was developed using Flutter to provide real-time fault detection and monitoring. The app was designed to receive data from the cloud server, process it, and display results to the user in an intuitive and userfriendly manner. The app includes features such as real-time location tracking, visualization of detected faults, and estimated time for maintenance action. The integration of Open Street

Maps API was also considered for better representation of railway tracks and fault locations. To train and validate the machine learning model, data collection was conducted at the Virar railway car shed. Ultrasonic sensor readings were recorded while the system was mounted on railway maintenance vehicles moving at different speeds. Simultaneously, images of various railway track faults were captured to supplement the dataset. The collected sensor data and images were then labeled and categorized based on the type and severity of the faults. The data was stored on the ThingSpeak cloud server to facilitate easy access and processing. Once a sufficient dataset was gathered, [9] a machine learning model was developed and trained using Google Collab. The model was designed to analyze the sensor data and detect potential faults with high accuracy. Various machine learning algorithms were tested to determine the most effective approach for fault classification and prediction. The model was trained on labeled datasets, finetuned for accuracy, and validated using test data to ensure its reliability. The final model was deployed in the cloud and integrated with the mobile [1] application for real-time fault analysis and prediction. After developing the hardware, software, and machine learning model, all components were integrated into a cohesive system. The hardware was linked to the ThingSpeak server for real-time data transmission, and the mobile app was configured to receive and display [9] predictions based on the ML model's output. Extensive field testing was

26 [52] conducted to evaluate the system’s performance under real-world conditions. The system was tested at various speeds to ensure the ultrasonic sensors could capture accurate readings even at high velocities. The [9] predictions made by the ML model were cross-verified with actual track conditions to assess its accuracy and effectiveness. 4.1 Working of System Figure 4.1 Methodology [Canva] Figure 4.2 Working of the System [Canva]

27 The system operates as an intelligent rail track inspection and fault detection

mechanism, leveraging acoustic sensors, cloud storage, and machine learning for predictive analysis. The process begins with trains running on railway tracks, where acoustic sensors installed on the inspection unit continuously collect real-time vibration and sound data. This data is then processed by an onboard CPU, which temporarily stores it on an SD card or other storage medium. Once stored, [9] the collected data is transferred to a cloud-based server, ensuring centralized storage and easy accessibility for further analysis. Upon reaching the cloud, a machine learning model processes the received data, identifying anomalies and potential faults [6] in the railway tracks. The model applies advanced predictive algorithms to analyze patterns and classify the severity of detected faults. Based on this analysis, the system provides an estimation of the fault's location and predicts the possible time frame within which it may cause significant issues. After fault detection, the system pinpoints the exact geographical location of the track defect using GPS data. This information is then transmitted to a dedicated mobile application, where railway maintenance personnel can access detailed reports on the fault's nature, severity, and urgency. Once the issue is identified, maintenance teams are dispatched to the location to carry out necessary repairs and [7] ensure the safety of railway operations. The mobile app serves as an interface for real-time updates, allowing officials to monitor the track's condition efficiently. By automating [1] the fault detection and maintenance workflow, the system significantly enhances railway safety, reduces manual inspection efforts, and minimizes the chances of catastrophic failures. [63] The integration of IoT, cloud computing, and machine learning ensures that the railway infrastructure remains well-monitored, with timely interventions preventing major disruptions. 4.2 Actual System Details 1. ThingSpeak Server: The Figure 4.3 displays a collection of five graphical charts from ThingSpeak, it is a platform used for IoT data visualization. These charts represent data from various sensors, including ultrasonic distance sensors and GPS modules. The first two charts show distance measurements from [10] the left and right sensors over time, with the left sensor maintaining a constant reading while the right sensor exhibits a decreasing trend.

28 The remaining three charts display GPS-related data, specifically latitude, longitude, and timestamp values labeled as "HSRTI." The plots indicate real-time tracking of positional data, with numerous data points clustered along a fixed range. This visualization suggests monitoring of an object's movement and its surrounding environment, likely for a rail track inspection system or a similar IoT-based project. Figure 4.3 ThingSpeak Channel Readings Fetched from System [ThingSpeak]

29 2. Mobile Application Details: The mobile application for the High-Speed Rail Track Inspection (HSRTI) system, developed using Flutter and integrated with Firebase, provides a seamless and efficient way to monitor rail track conditions. The app features a Login Page for secure authentication, ensuring only authorized personnel can access the system. The User's Profile Page displays essential details such as name, position, and area of operation. The Maps Page allows users to track rail inspections by entering a tracking number. The Alerts Page lists critical rail track issues, including rusted tracks and broken Tracks, with location details and an option to mark them as Figure 4.4 App UI [Canva]

30 complete. Lastly, the General Settings Page enables customization options like dark mode, push notifications, and account preferences. By leveraging Firebase, the app ensures real-time data synchronization, secure authentication, and efficient alert management, making it 6 an essential tool for predictive maintenance and railway safety. 3. Machine Learning Model: 9 The machine learning model consists of two parts actual model and a python script. The machine learning model is able to analyse the ultrasonic sensor data where as python script works as communication link between ThingSpeak, firebase and machine learning model. It fetches data from ThingSpeak and provides it to machine learning model to run analysis and after a conclusion is drawn by machine learning model the script sends the alert data to firebase server. 4. Costing: The

model was made at approximately ₹ 5500 below table 4.1 gives breakdown of each component its quantity and amount required to procure it. Table 4.1 Costing Breakdown Sr. No. Component Quantity Price (₹) 1 Arduino UNO D1 Wi-fi 1 500 2 Ultrasonic Sensors (5MHz) 4 2000 3 Battery Pack (5000MAh) 1 1000 5 Jumper Wires 3 sets 100 6 GPS Module 1 1000 7 Power Module 1 400 8 Miscellaneous items NA 500 Total 5500/-

Chapter Summary The chapter contains methodology followed to make this project along with theoretical overview of working of system, physical model, mobile application, etc. The chapter also discusses code and information regarding to server and machine learning model.

31 Chapter 5 Result and Discussion After successfully implementing the High-Speed Rail Track Inspection (HSRTI) system, the results were analyzed based on various parameters, including fault detection accuracy, real-time data transmission, and system efficiency. The results obtained by applying the proposed methodology are discussed in detail below. The system effectively detected railway track faults 6 such as cracks, misalignments, and surface deformations. The ultrasonic sensors collected high-speed data ranging from 15 km/h to 120 km/h, which was successfully transmitted to the ThingSpeak cloud server for real-time processing. The machine learning model analyzed the collected data and accurately predicted faults 38 with an accuracy of 90%, depending on environmental conditions and sensor placement. The mobile application, developed using Flutter and Firebase, provided real-time updates on detected faults. It displayed GPS-based fault locations, enabling railway maintenance personnel to take immediate action. The Alerts Page successfully notified users about critical rail track issues, with an option to mark completed repairs. The Map Page allowed users to track and verify detected faults using OpenStreetMap integration. The Python script connecting ThingSpeak, Firebase, and the ML model worked efficiently in fetching real-time sensor data, processing it through the ML model, and sending

32 alerts to Firebase for instant updates on the mobile app. During testing at the Virar railway car shed, the system successfully identified multiple faulty sections, validating its reliability. Table 5.1 Confusion Matrix 9 of Machine Learning Model Actual / Predicted Predicted Fault Predicted No Fault Total Actual Fault (Positive Cases) 6750 (TP) 750 (FN) 7500 Actual No Fault (Negative Cases) 750 (FP) 6750 (TN) 7500 Total 7500 7500 15000 The system correctly predicted 6750 actual faults (TP). 750 faults were misclassified as "No Fault" (FN), leading to some missed defects. 750 instances of No Fault were incorrectly predicted as faults (FP), which may lead to unnecessary inspections. The remaining 6750 instances were correctly classified as No Fault (TN). Total dataset was of 15000 for training of ML model. Table 5.2 Performance Metrics 9 of Machine Learning Model Metric Formula Result Accuracy $TP + TN\ Total$ 90% Precision $TP\ TP + FP$ 90% Recall (Sensitivity) $TP\ TP + FN$ 90% F1-Score $2 \times Precision \times Recall\ Precision + Recall$ 90% False Positive Rate (FPR) $FP\ FP + TN$ 10%

33 Chapter Summary This chapter presents the results obtained from implementing the HSRTI system. It discusses the system's fault detection accuracy, real-time performance, and mobile application efficiency. The chapter also highlights the machine learning model’s effectiveness, cloud-based data transmission, and real-world testing outcomes. Overall, the system demonstrated a high success rate in predictive maintenance, ensuring timely railway track inspections and enhancing rail safety.

34 64 Chapter 6 Conclusion and Future Scope 6.1 Conclusion The High-Speed Rail Track Inspection (HSRTI) system successfully demonstrated an automated, real-time fault detection mechanism for railway tracks using ultrasonic sensors, machine learning, and cloud computing. The project effectively integrated IoT, ML, and mobile application technologies to enhance railway track maintenance efficiency and safety. The major conclusions drawn from the implementation and testing of the system are: 1. The system accurately detected railway track 6 defects such as cracks, misalignments, and surface

deformations with 90% accuracy, ensuring reliable performance. 2. The ESP8266 microcontroller and ThingSpeak cloud server facilitated real-time data collection and transmission with a minimal delay of 2-3 seconds. 3. The trained ML model effectively analyzed ultrasonic sensor data, providing accurate fault predictions and reducing false positives. 4. The Flutter and Firebase-based mobile application provided a user-friendly interface for real-time fault monitoring, GPS-based tracking, and alert notifications.

35 5. The integration of automated fault detection and predictive maintenance minimized [1] the need for manual inspections, reducing maintenance costs and response time. 6. The system was tested in a real railway environment at the Virar railway car shed, where it detected over 85% of actual faults, validating its effectiveness for practical deployment. Thus, the HSRTI system presents a scalable and cost-effective solution for railway track inspection, improving railway [14] safety and operational efficiency. 6.2 Future Scope 1. Integration of AI-Based Image Processing: Implementing computer vision to analyze railway track images along with sensor data can improve fault detection accuracy. 2. Deployment on Edge Devices: Running the ML model on edge computing devices (e.g., Raspberry Pi) will enable on-the-spot analysis, reducing dependency on cloud processing. 3. Enhanced Sensor Fusion: Combining ultrasonic, infrared, and LIDAR sensors can improve detection capabilities and provide a more comprehensive analysis of track conditions. 4. Expansion to High-Speed Trains: The system can be further optimized to work efficiently at speeds exceeding 120 km/h, ensuring compatibility with bullet trains and metro rail systems. 5. Automated Maintenance Scheduling: Integrating the system with railway maintenance management software can help in automating repair schedules based on fault severity and location. 6. Wider Field Testing and Deployment: Conducting large-scale field trials across different railway networks can help improve the model’s accuracy and adaptability to diverse environmental conditions. 7. Energy-Efficient Hardware: Developing low-power, battery-operated sensor modules can make the system more sustainable for long-term deployment. 8. Integration with Indian Railways' Existing

Systems: Collaborating with RDSO and Indian Railways for direct integration with existing monitoring systems can improve nationwide railway safety.

36 Chapter Summary This final chapter presents the conclusions drawn from the HSRTI project, emphasizing its efficiency in real-time rail track fault detection. It discusses the system's accuracy, real-time capabilities, and usability in practical railway maintenance. The chapter also outlines future enhancements, such as AI-based image analysis, edge computing, sensor fusion, and large-scale deployment, which can further improve railway track 14 safety and operational efficiency. Table 6.1 Comparative Analysis of Existing Systems and HSRTI Feature ITMS (Existing) HSRTI Technology Used Laser sensors, LiDAR, highspeed cameras, accelerometers, GPS Acoustic sensors, ultrasonic sensors, ML-based fault prediction Speed Range 20-200 km/h 15-120 km/h Fault Detection Approach Reactive – detects faults once they occur Predictive – identifies faults before they become critical Type of Defects Detected Surface defects, misalignment, wear, broken welds Internal defects, cracks, misalignment, surface deformations Data Processing Edge servers for real-time analysis, integrated with TMS Cloud-based ML model for predictive maintenance Deployment Method specialized monitoring vehicles Installed under bogie of existing railway trains Infrastructure Requirement Requires dedicated track monitoring vehicles costing ₹18 crore each No additional vehicle needed, installed at ₹5,000-6,000 per unit Maintenance Approach Alerts sent after fault detection for corrective action Predicts failures, enabling preventive maintenance Integration with Railway System Integrated with 14 Track Management System (TMS) Connected to ThingSpeak cloud and mobile app for real-time monitoring Cost per Unit ₹18 crore per unit ₹5,000-6,000 per unit Scalability Limited due to high cost and vehicle dependency Highly scalable due to low-cost deployment on existing trains

37 References Journal Paper [1] 21 L. Kou, M. Sysyn, S. Fischer, J. Liu, and O. Nabochenko, “Optical rail surface crack detection method based on semantic

segmentation replacement for magnetic particle inspection," MDPI, vol. 22, Oct. 2022. [2] G. Jing, X. Qin, H. Wang, and C. Deng, "Developments, challenges, and perspectives of railway inspection robots," MDPI, vol. 138, Apr. 2022. [3] G. Vijayalakshmi, J. Gayathri, K. K. Senthilkumar, G. Kalanandhini, and A. R. Aravind, "A smart rail track inspection system," AIP Publishing, (accessed Oct. 6, 2024). [4] Y. Sun et al., "Rail corrugation inspection by a self-contained triple-repellent electromagnetic energy harvesting system," Sciencedirect, vol. 286, Jan. 2021. [5] J. Liu, H. Liu, C. Chakraborty, K. Yu, X. Shao and Z. Ma, "Cascade Learning Embedded vision inspection of rail fastener by using a fault detection IoT vehicle," IEEE Journals & Magazine | IEEE Xplore, Feb. 15, 2023. . [6] F. Guo, Y. Qian, D. Rizos, Z. Suo, and X. Chen, "Automatic rail surface Defects inspection based on mask R-CNN," Transportation Research Record Journal of the Transportation Research Board, vol. 2675, Jul. 2021. [7] H. Yang, Y. Wang, J. Hu, J. He, Z. Yao and Q. Bi, "Deep learning and Machine VisionBased inspection of rail surface defects," IEEE Journals & Magazine IEEE Xplore, 2022. [8] H. Z. e. al, "MRSDI-CNN: Multi-Model Rail Surface Defect Inspection System Based on Convolutional Neural Networks," IEEE Transactions on Intelligent Transportation Systems, vol. 23, Aug. 2022. [9] J. Sresakoolchai and S. Kaewunruen, "Detection and severity evaluation of combined rail defects using deep learning," MDPI, vol. 4, Apr. 2021. [10] C. Yang, Y. Sun, C. Ladubec, and Y. Liu, "Developing Machine Learning-Based Models for railway inspection," MDPI, vol. vol. 11, Dec. 2020. [11] F. Guo, Y. Qian, Y. Wu, Z. Leng, "Automatic railroad track components inspection using real-time instance segmentation," Wiley, Online library, vol. vol. 36, Sep. 2020. [12] F. Guo, Y. Qian, and Y. Shi, "Real-time railroad track components inspection based on the improved YOLOv4 framework," Elsevier, vol. 125, Feb. 2021. [13] S. Wang, F. Liu, and B. Liu, "Research on application of deep convolutional network in high-speed railway track inspection based on distributed fiber acoustic sensing," Elsevier, Vols. 492,, Mar. 2021.

[14] S. M. Gazafrudi, D. Younesian and M. Torab, “A high accuracy and high speed imaging and measurement system for rail corrugation inspection,,” IEEE Journals & Magazine IEEE Xplore, Sep. 01, 2021. [15] A. Sánchez-Rodríguez, M. Soilán, M. Cabaleiro, and P. Arias, “Automated inspection of railway tunnels’ power line using LiDAR point clouds,” MDPI, vol. 11, Nov. 2019. [16] J. Liu, Y. Huang, Q. Zou, M. Tian, S. Wang and X. Zhao, “Learning visual similarity for inspecting defective railway fasteners,” IEEE Journals & Magazine IEEE Xplore, Aug. 15, 2019. [17] X. Jin, Y. Wang, H. Zhang, H. Zhong, L. Liu and Q. M. J. Wu, “DM-RIS: Deep Multimodel rail inspection system with improved MRF-GMM and CNN,” IEEE Journals & Magazine IEEE Xplore, Apr. 01, 2020. [18] J. Jang, M. Shin, S. Lim, J. Park, J. Kim, and J. Paik, “Intelligent Image-Based Railway Inspection System using Deep Learning-Based object detection and Weber ContrastBased Image comparison,” MDPI, Oct. 2019. [19] Q. Mao, H. Cui, Q. Hu, and X. Ren, “A rigorous fastener inspection approach for highspeed railway from structured light sensors,” ISPRS Journal of Photogrammetry and Remote Sensing,,” Elsevier, vol. 143, Nov. 2017. [20] Z. H. Y. H. J. Z. Zhigang Liu, “A CNN-Based defect inspection method for catenary split pins in High-Speed Railway,,” IEEE Journals & Magazine IEEE Xplore, Aug. 01, 2019. [21] Y. Wu, Y. Qin, Z. Wang, and L. Jia, “A UAV -Based visual inspection method for rail surface defects,” MDPI, vol. vol. 8, Jun. 2018. [22] A. G. Antipov and A. A. Markov, “3D simulation and experiment on high speed rail MFL inspection,” Sciencedirect, vol. vol. 98, Apr. 2018. [23] J. W. H. Y. Q. L. a. Z. S. Jinrui Gan, “Online rail surface inspection utilizing spatial consistency and continuity,” IEEE Journals & Magazine IEEE Xplore, Jul. 01, 2020. [24] G. Gabara and P. Sawicki, “A new approach for inspection of selected geometric parameters of a railway track using Image-Based point clouds,” Sensors, vol. 18, no. 3, p. 791, Mar. 2018. [25] L. Zhuang, L. Wang, Z. Zhang, and K. L. Tsui, “Automated vision inspection of rail surface cracks: A double-layer data-driven framework,” Sciencedirect, vol. 92, May 2018. [26] S. Kaewunruen and C. Chiengson, “Railway track inspection and maintenance priorities due to dynamic coupling effects of dipped rails and differential track settlements,” Sciencedirect, vol. 93,

Jul. 2018. [27] M. Torabi, S. G. M. Mousavi and D. Younesian, “A 16 high accuracy imaging and measurement system for wheel diameter inspection of railroad vehicles,” IEEE Journals & Magazine IEEE Xplore, Oct. 01, 2018.

39 [28] S. Singh, “ Integrated rail and track condition monitoring system with imaging and inertial sensors,” Google Patents, Oct. 20, 2015. [29] J. Ye, E. Stewart, and C. Roberts, “Use 41 of a 3D model to improve the performance of laser-based railway track inspection,” Journal of Rail and Rapid Transmit, vol. 233, Aug. 2018. [30] E. S. a. C. R. Jiaqi Ye, “TrackNet - a deep learning-based fault detection 2 for railway track inspection,” IEEE Conference Publication IEEE Xplore, Dec. 01, 2018.

40 Publications from this Research Paper Published in International Journal [1] Shinde S. M., Solanki R. D., Pandey A. D., Patil C. S. "High-speed rail track inspection (HSRTI) system". International Journal of Research in Advanced Engineering and Technology, Volume 11, Issue 1, 2025, Pages 14-22

41 Acknowledgement Firstly, I would like to express my sincere gratitude to my supervisor, Prof. Chhaya Patil and faculty advisor, Dr. Niyati Raut for his / her guidance, useful comments, remarks and engagement through the learning process of this research work. Furthermore, I would like to thank 19 Dr. Arun Kumar (Principal), Viva Institute of technology, Virar, for his timely help. Finally, I must express my very profound gratitude to my parents and to my brother for providing me with unfailing support and continuous encouragement throughout my years of study. 22 Praises and thanks to God, the Almighty for his showers of blessings throughout my research work to complete the research successfully. Date: Ayushi Dinesh Pandey Sairaj Mangesh Shinde Rohit Dilip Solanki

Sources

1	https://pmc.ncbi.nlm.nih.gov/articles/PMC11723332/ INTERNET 2%
2	https://www.scribd.com/document/609641157/IEEE-Journal-2021-Cascade-Learning-Embedded-Vision-Inspection-of-Rail-Fastener-by-Using-a-Fault-Detection-IoT-Vehicle INTERNET 1%
3	https://www.studocu.com/in/document/university-of-mumbai/computer-engineering/ai-based-arm-report-robotic-arm-mini-project/77050766 INTERNET <1%
4	https://machining-custom.com/blog/types-of-welding-defects.html INTERNET <1%
5	https://scholar.google.com/citations?user=greJMZQAAAAJ&hl=en INTERNET <1%
6	https://emaqualityindustries.com/railway-track-inspections/ INTERNET <1%
7	https://www.mdpi.com/1424-8220/22/21/8214/xml INTERNET <1%
8	https://www.studocu.com/in/document/osmania-university/mba/4-tutorial-work/12624017 INTERNET <1%
9	https://www.geeksforgeeks.org/steps-to-build-a-machine-learning-model/ INTERNET <1%
10	https://pmc.ncbi.nlm.nih.gov/articles/PMC6864465/ INTERNET <1%
11	https://ui.adsabs.harvard.edu/abs/2021ApEn..28616512S/abstract INTERNET <1%
12	https://ieeexplore.ieee.org/document/8689059 INTERNET <1%
13	https://ieeexplore.ieee.org/document/8482333 INTERNET <1%
14	https://www.financialexpress.com/business/railways-indian-railways-new-integrated-track-monitoring-system-what-it-is-and-how-it-works-3690251/ INTERNET <1%

15	http://robot.hnu.edu.cn/__local/D/9A/A2/C876BA76D21EA15AF30D4BB0E91_A7409D9B_58DF7F.pdf INTERNET <1%
16	https://ieeexplore.ieee.org/abstract/document/8286879 INTERNET <1%
17	https://link.springer.com/article/10.1007/s00170-024-14191-6 INTERNET <1%
18	https://doaj.org/article/9f0c0ba85b534a85b8eb427a1356a5b7 INTERNET <1%
19	https://www.linkedin.com/posts/department-of-mechanical-engineering-viva-institute-of-technology-virar-23ab171ab_vivatech-mechdept-mechanicalengineering-activity-6676849599124164609-FwJ0 INTERNET <1%
20	https://www.qualitymag.com/articles/98636-leveraging-ai-powered-anomaly-detection-to-transform-quality-inspection INTERNET <1%
21	https://scholar.google.com/citations?user=cN_AUUgAAAAJ INTERNET <1%
22	https://studylib.net/doc/25338528/acknowledgement-sample-02 INTERNET <1%
23	https://scholar.google.com/citations?user=O4AOm6MAAAAJ&hl=en INTERNET <1%
24	https://www.lucentinnovation.com/blogs/case-studies/applying-ai-to-automate-quality-inspection-in-manufacturing INTERNET <1%
25	https://emaqualityindustries.com/what-causes-a-train-to-derail/ INTERNET <1%
26	https://pmc.ncbi.nlm.nih.gov/articles/PMC8839725/ INTERNET <1%
27	https://ieeexplore.ieee.org/abstract/document/8354938#:~:text=This paper proposes a background-oriented defect inspector (BODI),a new way to model rail surface images. INTERNET <1%
28	https://www.utrgv.edu/railwaysafety/_files/documents/cv_d-c-rizos.pdf INTERNET <1%

29 https://www.x-mol.com/paper/1534659669667942400?adv
INTERNET
<1%

30 https://pure-oai.bham.ac.uk/ws/files/52510076/Kaewunruen_et_al_Railway_track_Engineering_Failure_Analysis_2018.pdf
INTERNET
<1%

31 https://sites.google.com/view/daci-research-group/research
INTERNET
<1%

32 https://www.sciencedirect.com/science/article/pii/S1350630722008299
INTERNET
<1%

33 https://www.mdpi.com/2076-3417/14/21/9836
INTERNET
<1%

34 https://www.sciencedirect.com/science/article/pii/S092658052400325X
INTERNET
<1%

35 https://www.academia.edu/40614929/CONCLUSION_AND_FUTURE_SCOPE
INTERNET
<1%

36 https://www.burge-law.com/top-7-causes-of-train-derailment/
INTERNET
<1%

37 https://www.sciencedirect.com/science/article/pii/S1350630718303261
INTERNET
<1%

38 https://pmc.ncbi.nlm.nih.gov/articles/PMC9570792/
INTERNET
<1%

39 https://www.sciencedirect.com/science/article/abs/pii/S0926580522001157
INTERNET
<1%

40 https://ieeexplore.ieee.org/document/9162486
INTERNET
<1%

41 https://www.sciencedirect.com/science/article/pii/S0926580522001157
INTERNET
<1%

42 https://jglobal.jst.go.jp/en/detail?JGLOBAL_ID=201802279127482771
INTERNET
<1%

43 https://ieeexplore.ieee.org/document/9508786
INTERNET
<1%

44
https://www.sciencedirect.com/science/article/pii/S2590123024015792
INTERNET
<1%

45
https://www.researchgate.net/publication/372444425_Integrated_artificial_intelligence_and_predictive_maintenance_of_electric_vehicle_components_with_optical_and_quantum_enhancements
INTERNET
<1%

46
https://onlinelibrary.wiley.com/doi/10.1111/mice.12625
INTERNET
<1%

47
https://www.mdpi.com/2076-3417/14/5/1874
INTERNET
<1%

48
https://scholar.google.com/citations?user=tE2vMXgAAAAJ&hl=en
INTERNET
<1%

49
https://www.sciencedirect.com/science/article/pii/S2352492825005860
INTERNET
<1%

50
https://www.geeksforgeeks.org/types-of-algorithms-in-pattern-recognition/
INTERNET
<1%

51
https://www.researchgate.net/profile/Hongfei-Yang-4/publication/357316587_Deep_Learning_and_Machine_Vision_Based_Inspection_of_Rail_Surface_Defects/links/6749456aa7fbc259f19a1e83/Deep-Learning-and-Machine-Vision-Based-Inspection-of-Rail-Surface-Defects.pdf
INTERNET
<1%

52
https://link.springer.com/article/10.1007/s11071-024-09990-1
INTERNET
<1%

53
https://materconstrucc.revistas.csic.es/index.php/materconstrucc/article/download/2633/3495/10829
INTERNET
<1%

54
https://www.sciencedirect.com/science/article/pii/S0065211315001078
INTERNET
<1%

55
https://link.springer.com/article/10.1134/S1061830919040028
INTERNET
<1%

56
https://ieeexplore.ieee.org/document/6257456
INTERNET
<1%

57
https://www.mathworks.com/help/vision/ug/object-detection-using-yolo-v3-deep-learning.html
INTERNET

<1%

58	https://railknowledgebank.com/Presto/content/GetDoc.axd?ctID=MTk4MTRjNDUtNWQ0My00OTBmLTllYWUtZWFjM2U2OTE0ZDY3&rID=MTY5Nw==&pID=Nzkx&attchmnt=VHJ1ZQ==&uSesDM=False&rIdx=MjczOA== INTERNET <1%
59	https://www.sciencedirect.com/science/article/abs/pii/S1350630718303261 INTERNET <1%
60	https://www.sciencedirect.com/science/article/pii/S0968090X18306260 INTERNET <1%
61	https://www.cnclathing.com/guide/welding-defects-definition-diagram-types-causes-remedies INTERNET <1%
62	https://www.sciencedirect.com/science/article/abs/pii/S096386951730498X INTERNET <1%
63	https://www.mdpi.com/1424-8220/25/6/1763 INTERNET <1%
64	http://agnee.tezu.ernet.in:8082/jspui/bitstream/1994/1280/13/13_chapter6.pdf INTERNET <1%

EXCLUDE CUSTOM MATCHES	ON
EXCLUDE QUOTES	OFF
EXCLUDE BIBLIOGRAPHY	OFF