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Original Article

Hybrid Deep Learning Approach for Early Detection of Railway Track Faults to Enhance Railway Safety

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Abstract - Railway tracks are the primary infrastructure that allows trains to move and any defect in the railway track can lead to minor or major accidents. Consistent monitoring and condition-based maintenance are crucial for safety and minimizing hazards. In this paper, an automated fault detection system is proposed for railway track fault diagnosis using Hybrid RF+LSTM model based on the Railway Track Fault Detection (RTFD) dataset. Class imbalance is handled by noise removal, normalization, encoding features, and balancing with SMOTE, while the dataset's quality is enhanced. Their proposed hybrid model combines Random Forest and Long Short-Term Memory (LSTM) to model sequential dependencies, leading to improved classification accuracy. Prior ML and DL models, such as CNN, ResNet-50, and VGG16, are applied for evaluate model's performance. With scores of 98% for accuracy, 96% for precision, 98% for recall, and 97% for F1-score, the Hybrid RF+LSTM model surpasses all other models in the experiments. Research like this lends credence to the idea that the proposed method could greatly enhance railway safety and reliability by making track defects much easier to spot.

Keywords - Railway Track Inspection, Spectrograms, Acoustic Signals, Machine Learning, Fault Diagnosis.

1. Introduction

The development of railway infrastructure is crucial to growth of economies worldwide and is a vital part of modern transportation systems [1]. Getting products and people from point A to point B is easier, cheaper, and better for the environment when use railways. With the rapid growth of urbanization and industrialization, the demand for safe and efficient railway transportation has increased considerably [2]. However, railway tracks are continuously exposed to environmental conditions, heavy mechanical stress, vibration, and material degradation, which may lead to cracks, corrugation, ballast discontinuities, and other structural defects [3]. These defects can cause severe railway accidents, derailments, service interruptions, and economic losses.

The traditional method of railway track inspections is manual or with the help of sensor based monitoring, such as ultrasonic testing or eddy current testing [4]. These techniques have been extensively adopted but are typically labor-intensive, inefficient, costly and human-intensive [5]. Manual inspections also have the risk of subjectivity and inconsistencies, especially in large-scale railway networks [6]. Also, age old infrastructure and growing train traffic has made the inspection processes very complex, making the conventional monitoring methods inadequate for real-time and accurate fault detection [7]. As a result, automatic and intelligent railway track monitoring systems are becoming increasingly important to enhance safety and cut maintenance expenses [8][9].

In recent years, there is a great deal of interest in railway fault detection and structural health monitoring using ML and DL because of their efficient processing of large-scale railway data, abnormal track detection, and the ability to enhance classification accuracy through automatic learning mechanisms [10][11]. The advantage of ML and DL over traditional inspection techniques is low detection error, quicker analysis, less human participation, and higher reliability [12][13]. These intelligent technologies can distinguish between train tracks that are damaged and those that are not, provide back-end support for monitoring apps that run in real-time, and allow for the early detection of rail faults before they worsen [14]. In order to reduce the likelihood of accidents, minimize damage to the railway infrastructure and maintenance expenses, increase safety in railway system, and enhance the general dependability and effectiveness of contemporary smart railway transportation systems, fault detection systems based on ML and DL are essential.

1.1. Motivation and Contribution

This study is motivated because of the growing number of railway accidents occurring due to railway track defects and the need for accurate and automated railway fault detection systems. Railway inspection procedures are labor-intensive, time-consuming, and don't always provide real-time status monitoring. More precise and dependable early fault identification of railway tracks has been made possible by recent advancements in DL and ML. The effort is motivated by the need to construct an intelligent defect detection framework for railways. This framework helps with railway safety, maintenance cost, and preventive maintenance. This research offers several key contributions as listed below:

- The RTFD dataset is utilized to build a real-time framework to improve railway safety and reliability by identifying flaws in railway tracks.
- The implementation of a thorough pretreatment pipeline involves noise removal, normalization,

feature encoding, and SMOTE-based balancing in order to properly handle class imbalance.
- A hybrid approach for sequential pattern learning and feature selection is proposed (RF+LSTM), where an RF is used to select the features to be processed by an LSTM network.
- The model's efficiency is evaluated using a range of performance metrics to provide a comprehensive and comprehensive evaluation of model.
- The findings of study improve capabilities of automated railway monitoring systems, aiding in the maintenance of railway infrastructure to ensure its safety and efficiency.

The motivation for the proposed work is found in the fact that the traditional and single-model methods used for railway track fault detection are unable to adequately capture feature importance and temporal dependencies. The study's innovation lies in the use of a unique hybrid RF+LSTM technique, which combines the two approaches into one to improve classification accuracy. Unlike traditional models, the proposed method takes advantage of the interaction between RF and LSTM to achieve better detection accuracy and robustness. It is a hybrid approach which achieves a better generalization performance on imbalanced datasets with preprocessing using SMOTE. In general, the proposed solution is a novel and valid solution for reliable, high accuracy railway track defect detection.

1.2. Organization of the Paper

The paper is structured in the following way: In Section II, related works for railway track defect detection are summarized, in Section III, the used dataset, preprocessing, and implementation of the model are presented, in Section IV, untried outcomes and comparison are shown, and in Section V, key findings of study and future research directions are summarized.

2. Literature Review

The key research projects and studies conducted about railway track defect detection are thoroughly reviewed and analyzed to guide and enhance development in this study.

A. S et al. (2026) acquired sensor data are preprocessed, transformed into discriminative features, and analyzed using a supervised classification approach to distinguish between normal and faulty track conditions. A 96.4% success rate in fault detection with few false alarms is demonstrated experimentally. Upon fault detection, severity indicators and location information obtained using GPS are transmitted wirelessly to a centralized monitoring platform for timely maintenance actions [15].

S. S et al. (2025) aimed to support railway safety management by accurately predicting accident severity and rescue resource allocation. Experiments show the possibility of an 83% track fault detection rate and a 91% severity classification rate which is unique in that the system incorporates both structured and unstructured data [16]. S. Sali et al. (2025) trained Machine learning algorithms, which classify them and detect defects including cracks, fractured pieces, loose fasteners etc. A Raspberry Pi-based controller coordinates data processing and communicates with cloud infrastructure. These extracted features are uploaded on cloud and all the defects detected by the AI Model can be visualized using a dashboard. This system has an accuracy of 94% which detects railway defects efficiently [17].

R. Thinakaran et al. (2024) aimed to the internet of things technology added modern and accurate fault-finding feature in the system. The accuracy rate of fault and crack detection is around 97%, which is for 2 mm crack. Along with this GPS module accurately track fault location [18]. G. Kaur et al. (2024) used a dataset of 384 images, with 30 iterations in training and batch size of 16. The default rates for learning are used in this analysis. Through careful testing, the paper demonstrates the ability of the ResNet50V2 model to distinguish railway track faults accurately, it achieves an accuracy rate of 86%. The study discovers the possibility of deep learning models including ResNet50V2 enhancing efficiency and reliability for railway track fault detection systems [19].

N Mukhtiar et al. (2023) This methodology classifies data as either faulty or non-faulty by comparing two ML algorithms: Density-Based Spatial Clustering of Applications Using K-means Clustering and Noise. The best method, with an accuracy of more than 95%, is K-means clustering [20]. M Yilmazer and M Karakose, (2023) The data set includes measurements that were taken in a range of lighting situations. To top it all off, the OpenCV library gets rid of video tremors and stabilizes the video during data collecting. Thus, with a mAP of 94.5%, the suggested method has demonstrated the ability to detect mistakes across numerous railway components [21].

Table I summarizes the recent research studies on railway track defect detection, gives proposed models, data used in the studies, major conclusions and challenges faced.

Table 1. Recent Studies on Railway Track Defect Detection Using Machine Learning Techniques

Author	Proposed Work	Results	Key Findings	Limitations & Future Work
A. S et al. (2026)	Developed a sensor-based railway fault detection system using supervised classification and GPS-enabled monitoring.	Achieved 96.4% fault detection accuracy with minimal false alarms.	Demonstrated efficient real-time fault detection and wireless fault reporting for maintenance support.	Future research can concentrate on enhancing scalability and integrating cutting-edge AI-based predictive maintenance systems.
S. S et al. (2025)	Proposed a railway safety framework using structured and unstructured data for accident severity prediction	Obtained 83% fault detection rate and 91% severity classification	Showed effectiveness of combining multiple data types for real-time railway safety	Vision Transformers and attention mechanisms can be integrated to further improve prediction

	and resource allocation.	accuracy.	management.	performance.
Sali et al. (2025)	Developed a Raspberry Pi and cloud-based railway defect detection system using machine learning algorithms.	Achieved 94% accuracy in detecting cracks, fractured parts, and loose fasteners.	Enabled real-time visualization of detected faults through cloud dashboards.	Future enhancement may include larger datasets and advanced deep learning models for higher robustness.
R. Thinakaran et al. (2024)	Implemented an IoT-based railway crack detection system using sensors, GPS, and GSM modules.	Achieved nearly 97% accuracy for detecting 2 mm cracks.	Demonstrated accurate fault localization and rapid alert transmission for railway safety.	System performance can be improved for detecting smaller cracks under varying environmental conditions.
G. Kaur et al. (2024)	Utilized imagine datasets to apply the ResNet50V2 deep learning model for railway track fault classification.	Achieved 86% classification accuracy.	Showed the capability of DL models in improving railway fault detection reliability.	Performance can be enhanced using larger datasets and optimized hyperparameter tuning.
N Mukhtiar et al. (2023)	Compared DBSCAN and K-means clustering algorithms for railway fault classification.	K-means clustering achieved over 95% accuracy.	K-means is identified as more effective for distinguishing faulty and non-faulty railway data.	Future work can integrate hybrid clustering and DL techniques for improved detection.
M Yilmazer and M Karakose (2023)	Proposed a railway fault detection method using OpenCV-based video stabilization under varying lighting conditions.	Achieved 94.5% mAP performance.	Demonstrated effective railway component fault detection through stabilized video analysis.	Further research can focus on improving detection accuracy under extreme environmental and vibration conditions.

Research gaps: Current research on defect detection in railway tracks reveals drawbacks, indicating the need for further research. Complex feature interactions are difficult for traditional ML models to capture, while DL algorithms need a lot of data and have significant processing costs. In addition, many of the approaches concentrate either on feature extraction or sequence learning without considering the others, which results in suboptimal performance. Poor research for solving the problem of class imbalance, lack of practical application in real railway environment is also present. Thus, the need for an efficient hybrid model which combines feature selection and temporal learning for more accurate and robust fault detection.

3. Research Methodology

The proposed methodology uses Railway Track Fault Detection (RTFD) dataset with preprocessing steps including noise removal, normalization, SMOTE-based balancing, and feature encoding to improve data quality. To improve performance of fault classification, a Hybrid RF+LSTM model is applied for extract features and learn sequential patterns. Accuracy, precision, recall, and F1-score are used to evaluate the model. The suggested railway track defect detection system is presented overall workflow in Fig. 1.

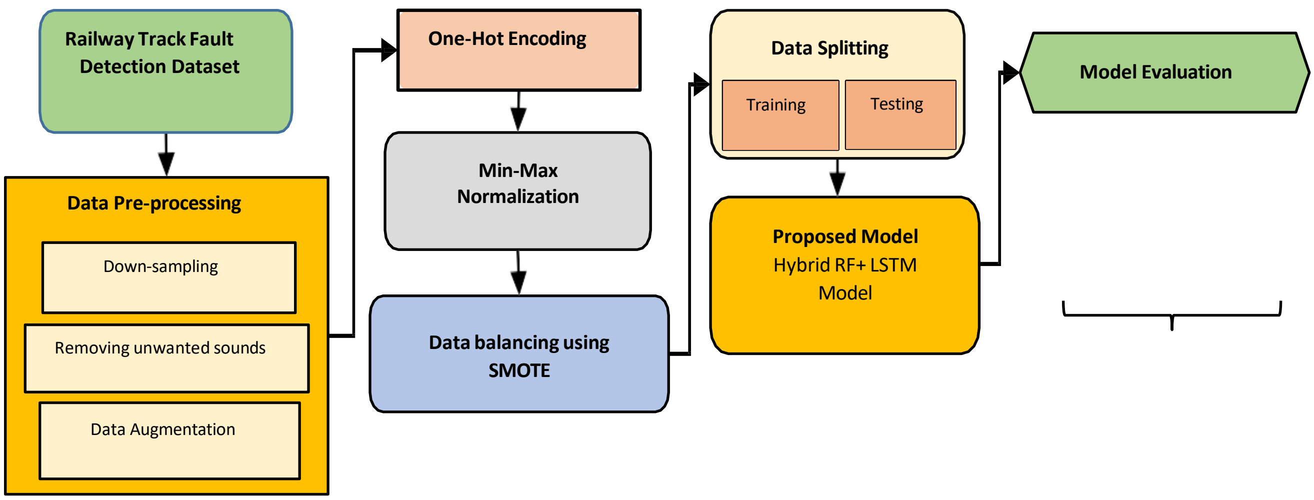

Figure 1. Proposed flowchart for railway track defect detection using DL

The next section provides detailed description of each step of proposed methodology:

3.1. Data Gathering and Analysis

The RTFD dataset [22] on Kaggle consists of railway track images that are divided into two classes: Defective and Non defective. The data comes from railway tracks in Bangladesh for the automation of fault detection using DL techniques. Has 150 images for each class (defective and non-defective), and 31 images per class for validation and 11 images per class for testing. The data set is used to create models to diagnose railway track defects, and to enhance railway safety. Below are a number of visualization methods used to analyze the distribution of data and the relationships of features.

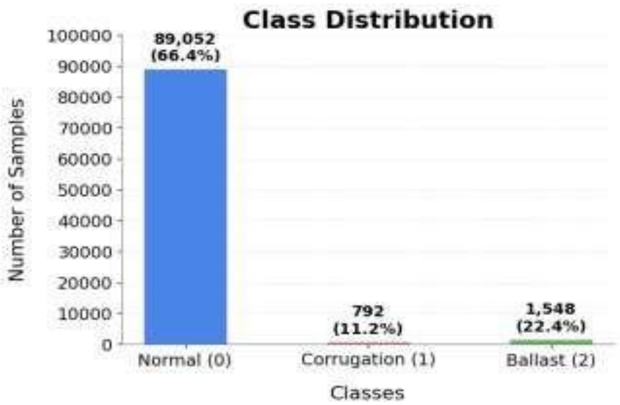

Figure 2. Bar Graph of Class Distribution of Railway Track Fault Detection (RTFD) Dataset

The class distribution of Railway Track Fault is shown in Fig. 2 and the data is characterized by high class imbalance with much more data in the Normal class than in the Corrugation and Ballast classes.

Figure 3. Sample Images of Defective and Non-Defective Railway Tracks

The sample images of RTFD are shown in Fig 3, where railway tracks with and without defects are presented. The defective samples consist of visually recognized track damages, such as cracks, alignment problems and structural defects, and the non-defective samples represent normal track conditions in a railway.

3.2. Data Pre-Processing

The RTFD dataset is used for data preparation, including data cleansing, labeling, normalization, and feature engineering. The preprocessing involved removing noise, resizing and normalizing the images to maintain consistency, and augmenting the data by rotating and flipping images to enhance dataset diversity and model performance. The steps taken enhanced the defect detection model's precision and reliability.

- Removing unwanted sounds: The unwanted sounds are removed in order to reduce the background noise and irrelevant noise sounds from the railway track, so as to improve the clarity and quality of the railway track fault signals.
- Down-sampling: Down-sampling is a data processing method that aims to lower the sampling rate of the input signals, thus lowering the data size and the computational complexity of the data while keeping the main properties of the signal.
- Data Augmentation: The model's robustness and generalizability are enhanced through data augmentation, which is executed using TensorFlow Keras. As a result, there are more training samples and a wider variety of data. Using a rescaling ratio of 1/255, the training images are normalized and scaled to 300×300 pixels. Modified copies of the original photos are produced using a range of augmentation methods, such as rotation, shearing, zooming, width and height shifting, and horizontal and vertical flipping. These techniques are similar to those used in signal processing, which include noise addition, pitch shifting, and time stretching. There were 299 images in the augmented training dataset, split evenly between two classes, with a batch size of 16. In contrast, the validation dataset had 62 images and the testing dataset had 22 images, with the sole change being rescaling to maintain the original image attributes.

3.3. Data Encoding using One-hot Encoding

Data encoding technique ensured that each fault category is represented uniquely without introducing ordinal relationships between classes. Binary vector representations that are well-suited for use in ML and DL models are created by applying one-hot encoding to categorical class labels.

3.4. Data Normalization using Min-Max Normalization

The feature values are scaled within range of 0 to 1 by normalizing the records using the min-max normalization approach. This process is carried out to enhance classifier performance, improve training efficiency, and reduce the influence of outliers in the dataset. The normalization process is performed using the following mathematical Equation (1).

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

The feature's minimum value $Xmin$ and its maximum value $Xmax$ are calculated from the original value (X), the normalized value X', and the following.

3.5. Data balancing using Synthetic Minority Oversampling Technique (SMOTE)

Data balancing involves changing distribution of classes to enhance performance of ML model. This is done when there is an imbalance in the dataset, meaning that one class contains many fewer samples than the others. SMOTE, is used to balance dataset and address class imbalance. By estimating the distance between a data point and its KNN in feature space, SMOTE creates fresh synthetic samples for the minority classes. Overfitting was reduced and model generalization was improved by using this strategy, which provided different training samples without duplicating existing data. The final dataset contained 33,000 healthy samples, 6,000 corrugation samples, and 12,000 ballast discontinuity samples, resulting in a balanced dataset of 51,000 samples, as shown in Fig. 4.

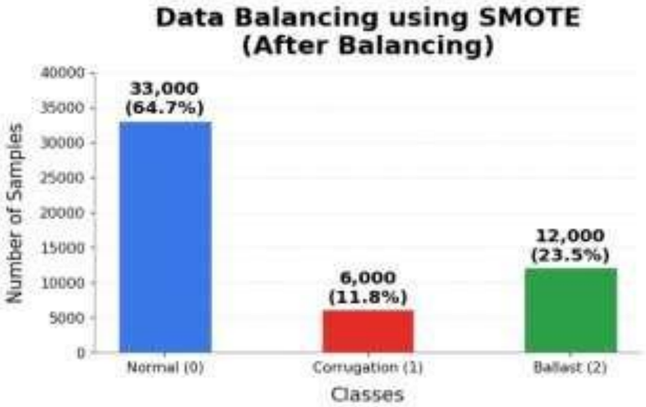

Figure 4. Data Balancing of Railway Track Fault Detection Dataset Using SMOTE

3.6. Data Splitting

A stratified 70:30 split is applied to partition dataset into train and test sets. The original set's distribution is replicated in the second set using this stratified sampling method, which maintains the same class distribution.

3.7. Implementation of the Model

A Hybrid RF+LSTM model is suggested and implemented to detect and classify the railway track faults efficiently. The implementation process consisted of feature extraction using Random Forest, sequential pattern learning, and finally the prediction using LSTM network.

3.6.1. Random Forest (RF) Model

An ensemble machine learning method called RF uses the strength of many decision trees to accomplish more reliable and accurate classification and prediction tasks. The trees are train on a random subset of features and set of trees, and each tree's features are chosen from this, and final prediction is computed by majority voting. The ability to deal with high dimensional data, to avoid overfitting, and important features associated with railway track faults is particularly advantageous for RF. The suggested study uses RF to analyze complicated feature relationships in order to improve fault classification procedure's reliability. The algorithm also optimizes the features in the dataset to make it more computational efficient. The mathematical expression of the model of the RF model is shown in Equation (2).

$$Y = mode\left(T_1(X), T_2(X), \dots \dots . T_N(X)\right) \qquad (2)$$

Each decision tree is represented by T_1, T_2, … … , T_N and Yˆ is the class predicted by majority voting.

3.6.2. Long Short-Term Memory (LSTM)

LSTM is one of the special Recurrent Neural Network (RNN) architectures that can identify sequential patterns and correlations in time series. LSTM selectively saves and forgets information during training using memory cells and gating methods, including input, forget, and output gates. For fault detection in railway tracks, LSTM can learn temporal features from audio or sensor sequences. Model is able to retain critical sequential information for longer periods and can be used to analyze railway vibration and acoustic signals. Moreover, LSTM eliminates the vanishing gradient problem usually faced by the conventional RNN model, which enhances the predictability consistency. The mathematical formulation of the state of the LSTM is shown in Equation (3).

$$h_t = o_t \cdot \tanh(C_t) \quad (3)$$

In this place, ht is the outcome of the hidden state, ot is the outcome of the output gate and Ct is state of memory cell at time step t.

3.6.2. Hybrid RF+LSTM Model

The suggested Hybrid RF+LSTM model enhances railway track defect detection performance by combining LSTM model's sequential learning skills combined with RF model's feature extraction capabilities. The current approach is to first use RF to carry out feature importance analysis and initial classification, and then use the optimized features selected by RF to teach the temporal pattern and make the final classification by LSTM. This hybrid method increases the accuracy of classification, noise immunity and enhances model generalization. By combining RF and LSTM, the model leverages the statistical and sequential nature of railway track data, enabling efficient processing of both types of data. The combination of RF and LSTM allows model to efficiently process both statistical and sequential characteristics of railway track data. Moreover, the hybrid architecture outperforms the traditional standalone models of ML and DL comes to fault identification performance. The overall hybrid model formulation is shown in Equation (4).

$$Y_{Hybrid} = LSTM(RF(X)) \qquad (4)$$

The equation can be written as X=features used for training, RF(X) is the optimized features produced by the RF model, and Y_Hybrid is the final prediction produced by Hybrid RF+LSTM model.

To improve performance of railway track fault identification process, suggested Hybrid RF+LSTM model is configured with optimal hyperparameters. The LSTM network has 64 hidden units and a dropout rate of 0.3, while the RF is trained using 100 estimators, each with a maximum of 20 trees. To enhance convergence, model is train using batch size of 32 and learning rate of 0.001 for 50 epochs.

3.7. Evaluation Metrics

Performance metrics such as F1 score, precision(PRE), recall(REC), and accuracy(ACC) are often used to assess how well a classifier performs on a classification task. The confusion matrix, which includes counts of TP, FP, TN, and FN, is the source of these measures. A suitable metric would be the proportion of properly recognized cases to all instances in dataset. This proportion is calculated by summing all instances in the dataset, including both positive and negative results, as well as any false positives or negatives. This indicator measures how well the classifier performs in general:

- Accuracy: The trained model's accuracy is the proportion of instances for which it makes a correct prediction, relative to the dataset's overall input sample count. Equation (5) provides a mathematical representation of it.

$$ACC = \frac{TP + TN}{TP + FP + TN + FN} \quad (5)$$

- Precision: The percentage of TP forecasts among all positive predictions yields the model's precision. Equation (6) provides a mathematical expression for it, and it quantifies the classifier's effectiveness in correctly detecting positive classifications.

$$PRE = \frac{TP}{TP + FP} \quad (6)$$

- Recall: The term "recall" refers to percentage of TP in a dataset that were accurately predicted relative to total number of TP. Equation (7) represents this metric, which evaluates model's accuracy in identifying relevant positive samples.

$$REC = \frac{TP}{TP + FN} \quad (7)$$

- F1 score: The range of its values is from 0 to 1, with higher values suggesting higher classification effectiveness and mathematically expressed by Equation (8).

$$F1\ Score = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (8)$$

4. Results and Discussion

In this section, performance of suggested Hybrid RF+LSTM model is assessed, and experimental setup is described and explained in detail for railway track fault detection to highlight effectiveness and efficiency of proposed model.

4.1. Experimental Setup

A Microsoft Windows 11 operating system with an Intel Core i7-8700 CPU, an NVIDIA GeForce RTX 2080 Ti GPU, and 8GB of RAM is used for DL research. Python 3.6, NVIDIA CUDA Toolkit, and TensorFlow with GPU support are used to set up the experimental environment for effective model construction and evaluation.

4.2. Experimental Results

The proposed framework is evaluated and trained using the Railway Track Fault Detection data set, and its performance is assessed using accuracy, precision, recall, and F1-score, as indicated in Table II. The model proposed in this study is Hybrid RF+LSTM model with an accuracy of 98%, which significantly demonstrates model's capacity to correctly categorize railway track conditions. The model's ACC was 98%, PRE 96%, REC 98%, and F1 score 97%, with few false predictions, which indicated it performed well and reliably in categorization of railway tracks as defective or non-defective.

Table 2. Classifiction Results of the Railway Track Fault Detection (RTFD) Dataset

Matrix	Proposed Hybrid RF+LSTM Model
ACC	98
PRE	96
REC	98
F1-score	97

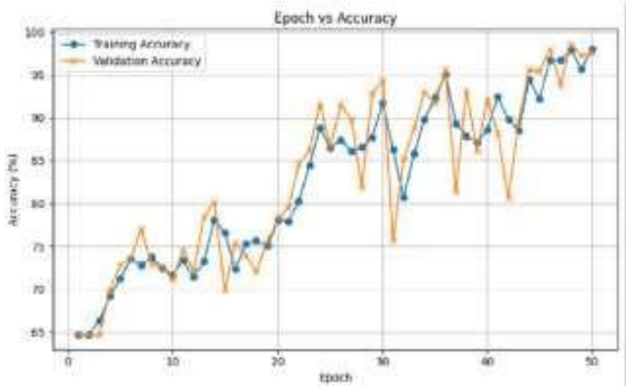

Figure 5. Accuracy curves of Hybrid RF+LSTM Model

Fig. 5 shows accuracy curve of Hybrid RF+LSTM model for 50 epochs of training and validation. As training continues, both the model is training well and converging as both training and validation accuracy are continuously rising. Although there were slight differences in the model's prediction accuracy in the validation tests, overall accuracy was close to 98%, indicating good classification performance and generalization.

Figure 6. Loss curves of Hybrid RF+LSTM Model

The train and val loss curves for Hybrid RF+LSTM model across 50 epochs are shown in Fig. 6. The model was successfully optimized and learned more effectively during training, as evidenced by the continuously declining loss values on both train and val sets. The validation loss shows a slight fluctuation, but declines over time, which indicates that model is well val and that prediction error is decreasing, suggesting the stability of convergence.

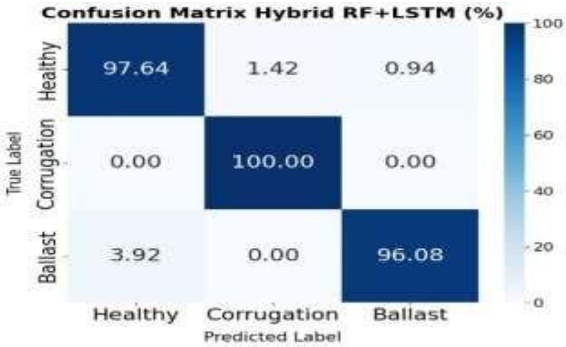

Figure 7. Confusion Matrix for the Hybrid RF+LSTM Model

The confusion matrix of Hybrid RF+LSTM model for identifying Healthy, Corrugation, and Ballast states is shown in Fig. 7. The model had a high classification accuracy, i.e., 96.08% for Ballast, 97.64% for Healthy and 100% for Corrugation, showing a strong predictive performance for all classes.

4.3. Comparative Analysis

The purpose of identifying railway track defects is to compare the suggested Hybrid RF+LSTM model to existing DL and ML models. ACC, PRE, REC, and F1-score were all above average for suggested model (98%, 96%, 98%, and 97%, respectively), indicating that it provided balanced and dependable classification. With accuracies over 91%, ResNet50 and VGG16 were successful. The hybrid model outperformed the CNN in precisely identifying railway defects shown in Table III, further demonstrating the efficacy of proposed methodology.

5. Conclusion and Future Study

The integrity of the railway track is one of the most important elements for safe, reliable and efficient railway operations. The traditional methods of inspection depend on manual inspection and regular testing process which may result in the detection of cracks, misalignment and deformities of the structure at a later stage. In this paper, a multi-sensor data fusion deep learning-based real-time railway track monitoring and fault identification method are proposed. The experimental results show that the deep learning models, including CNN (83%), ResNet-50 (91%) and VGG16 (91.2%) are getting moderate accuracy. However, proposed Hybrid RF+LSTM model obtained best accuracy of 98% suggesting it is more efficient in learning the feature importance and the sequential patterns for effective fault detection. For future research, the robustness of the system can be further improved by real-time deployment on the edge and further development of the sensor fusion algorithm, and by integrating EfficientNet, YOLO, Vision Transformer (ViT), and GRU models to analyze the large-scale monitoring of the railway and the detection of faults.

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