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Manyetik Sensörler ve Farklı Derin Öğrenme Modelleri Kullanarak Lastiklerin Çelik Kayışlarındaki Arıza Tespiti[1]

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Öz

Lastik arızaları önemli güvenlik riskleri oluşturur ve ileri seviye inceleme tekniklerini gerektirir. Bu araştırma, lastiklerin çelik kuşaklarındaki kusurları tespit etmek için manyetik sensörlerin ve derin öğrenmenin uygulanmasını incelemektedir. Kusurların neden olduğu manyetik alan değişimlerini yakalayarak, sağlam ve doğru bir arıza tespit sistemi geliştirilmesi amaçlanmaktadır. Bu çalışmada, manyetik görüntü sensör devresi tasarlanmış ve daha sonra ondan elde edilen görüntüler, hata olmayan, çatlak ve delaminasyon tipi çelik kuşak hataları olarak sınıflandırılmıştır. Çeşitli derin öğrenme modelleri ve bunların hibrit mimarileri araştırılmış ve karşılaştırılmıştır. Deneysel sonuçlar tüm modellerin güçlü bir performans sergilediğini, Transformatör modelinin %96.12'lik en yüksek doğruluğa ulaştığını göstermektedir. Geliştirilen sistem, endüstrilerde lastik güvenliğini iyileştirmek ve bakım maliyetlerini düşürmek için potansiyel bir çözüm sunmaktadır.

Anahtar kelimeler: Derin öğrenme, Çelik kayışlar, Manyetik sensör, Arıza tespiti

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Fault Detection in Steel Belts of Tires Using Magnetic Sensors and Different Deep Learning Models

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Abstract

Tire failures pose significant safety risks, necessitating advanced inspection techniques. This research investigates the application of magnetic sensors and deep learning for detecting defects in steel belts of the tires. It was aim to develop a robust and accurate fault detection system by measuring magnetic field variations caused by defects. In this study, the magnetic image sensor circuit had been designed and then the images obtained from it have been classified as none, crack, and delamination type steel belt errors. Various deep learning models and their hybrid architectures, were explored and compared. Experimental results demonstrate that all models exhibit strong performance, with the Transformer model achieving the highest accuracy of 96.12%. The developed system offers a potential solution for improving tire safety and reducing maintenance costs in industries.

Keywords: Deep learning, Steel belts, Magnetic sensor, Fault detection

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1. Introduction

Tires are essential components of modern transportation systems, ensuring vehicle stability, traction, and safety [1]. The steel belt, embedded within the tire's structure, is a critical component that provides reinforcement and load-bearing capacity. Defects in the steel belt may lead to catastrophic tire failures, posing significant risks to vehicle occupants and other road users. Early and accurate detection of these defects is crucial for preventing accidents and ensuring road safety [2]. There are frequent traffic accidents today and when we investigate the causes of these accidents, some of them are driver errors and the other large part is the damage to the car as a result of the vehicle not being inspected on time. One of these damages is the damage to the tires. There may be malfunctions such as wear and tear on the tires or a flat tire. One of these malfunctions is the damage to the steel belts inside the tire. The problem is that this damage is noticed late. Not detecting the damage to the steel belts early can also indirectly damage your vehicle. For example, if there is a break in the wires of the steel belts on your vehicle's tire and you drive your vehicle without noticing it, you will notice the following symptoms in your vehicle in the future [3]. These symptoms from the steering wheel shaking and if the damage is on the left tire, the vehicle pulls to the left, if the malfunction is on the right tire, the vehicle pulls to the right. Figure 1 represents a view of a steel belt in a tire.

Figure 1. An example of the steel belt of a tire

Traditional methods for inspecting steel belts, such as visual inspection and X-ray radiography, are time-consuming, labor-intensive, and often unable to detect hidden flaws. Current methods for inspecting tires are destructive because they require disassembly, making them impractical for in-service checks. Therefore, non-destructive and efficient techniques for detecting faults in steel belts are urgently needed [4]. Magnetic sensors offer a promising solution for this purpose by identifying changes in magnetic field patterns caused by defects like cracks, delaminations, and corrosion. Defects can be found and identified by analyzing these magnetic field fingerprints [5]. Deep learning is a potent tool for interpreting complicated data; it is well-known for its effectiveness in image and signal processing. Its capacity to identify high-level characteristics from unprocessed data makes it a potent contender for steel belt failure diagnosis. Using data from magnetic sensors and deep learning algorithms, reliable and precise defect detection models may be created. While several components have been the subject of flaw detection research, the use of deep learning and magnetic sensors to steel belt inspection is still mostly unexplored. The literature on reliable and efficient defect detection systems that make use of this mix of technologies is noticeably lacking. By assessing the viability and effectiveness of several deep learning models for using magnetic sensor data to identify flaws in steel belts, this paper aims to bridge that gap.

The primary objectives of this study are:

- To develop a magnetic image scanner to investigate the characteristics and potential of magnetic image sensors (MISs) for non-invasive detection of steel belt damage in tires.
- To investigate the performance of various deep learning models for this application.

- To evaluate the effectiveness of different feature extraction techniques for enhancing fault detection accuracy.
- To optimize the proposed system for real-world implementation, considering factors such as computational efficiency and robustness.

The remainder of this paper is organized as follows. Section 2 presents a literature review. Section 3 presents system implementation including magnetic image sensor design and the fault detection methodology. Section 4 presents the experimental results, including performance evaluation metrics and comparative analysis of different models. Section 5 discusses the performance of the results in brief. Finally, Section 6 summarizes the key findings, contributions, and potential future research directions.

2. Literature Review

Zhang et al. (2017) presented a research on the identification of tire flaws in multitextural radiography pictures [6]. They addressed the tire defect characterization problem using local regularity analysis and scale characteristic. A defect edge measurement model was used to identify the optimal scale and threshold parameters for defect edge detection. This framework separated faults from background textures. Finally, a novel approach for detecting tire problems was suggested using wavelet multiscale analysis. In order to effectively diagnose tire flaws, Zheng et al. (2021) presented a novel deep learning model called DCScNet [7]. This model offered advantages over regular CNNs, such as removing the requirement for labeled training data and lowering subjectivity in manually generated features, by substituting sparse coding for classic convolutional kernels. As a result, DCScNet performed better in categorization. Liu et al. (2022) combined the analysis of video and static image data to present a unique approach for diagnosing belt damage [8]. They created a deep learning framework for processing video data captured during on-site monitoring in order to detect damage from beginning to conclusion. While temporal convolutional networks (TCNs) extract dynamic information from consecutive video frames, improving detection accuracy by mitigating the effects of lighting conditions and shadows, an improved attention mechanism aids the model in focusing on relevant image regions despite complex backgrounds. Xie et al. (2021) developed an intelligent system combining deep learning for autonomous defect detection in order to automate the process of defect identification [9]. In order to overcome the shortcomings of conventional CNNs with sample-based data, they unveiled a new architecture known as Fusion Feature CNN (FFCNN), which is intended to extract and integrate pertinent features from sample inputs for accurate classification. Martínez-Parrales and Téllez-Anguiano (2022) developed an IoT-enabled malfunction detection system for conveyor belts [10]. The technology precisely calculated important characteristics such as stroke, direction, and frequency by measuring acceleration force at six vital spots on the machine using two-axis wireless accelerometers. By comparing these numbers to preset reference points, the system generated real-time visual warnings on the machine's state, both on-site and remotely. The system's efficacy was carefully tested by testing on an actual conveyor prototype. Lin (2023) described a revolutionary deep learning-based strategy for reliably detecting tire problems [2]. The suggested technology outperforms typical ShuffleNet architecture in terms of recognizing tire debris faults. When compared to other top models like GoogLeNet, VGGNet, ResNet, and the original ShuffleNet, the enhanced ShuffleNet obtains an impressive detection rate of 94.7%. This innovative solution benefits both drivers and tire producers by lowering labor costs and considerably speeding up the tire problem identification process. Zhang et al. (2023) introduced IDD-Net, a pioneering deep learning model created expressly to address the issues involved with industrial defect detection [3]. IDD-Net used a novel local-global backbone feature network (LGB-Net) to successfully resolve flaws with various degrees of similarity and diversity. Furthermore, the suggested Three-Layer Feature Aggregation network (TFLA-Net) efficiently addresses the issue of large scale changes in faults. TFLA-Net used a revolutionary three-layer descending approach to smoothly incorporate semantic and fine-grained information. To solve the issue of object loss deviation at different scales, a new IoU loss function, Defect-IoU loss, was proposed. This novel loss function adjusts the loss amount according to the area difference between objects of different sizes, resulting in a more balanced optimization process. Sedaghat et al. (2021) introduced a new strategy for identifying tire flaws in X-ray pictures based on an entropy filter, patch texture attributes extraction by Local Binary Pattern, and defect classification via Support Vector Machine (SVM) [11]. The suggested technique begins by applying an entropy filter to the input. The patch classifier identified the candidate areas, which were picked from the picture and had distinct patterns. All flaws were found and categorized, and the algorithm's efficiency was evaluated. Şener et al. (2022) presented a ground-breaking method for increasing car safety: a vision-based seat belt detector that changes the seat height without the driver or passenger's interaction [12]. The device assisted in preventing potentially catastrophic neck injuries caused by inappropriate seat belt positioning by properly recognizing the position of the seat belt relative to the driver's or passenger's neck. DenseNet121, GoogLeNet (Inception-v3), and ResNet50 were used in a comprehensive benchmarking procedure to assess the performance of several deep learning architectures. The models were evaluated according to their sensitivity, specificity, precision, false-positive rate, false-negative rate, F1 score, and accuracy. Furthermore, training and validation loss curves, as well as accuracy curves, were produced for each model to offer a thorough study of its performance. A noise reduction technique was introduced by Sun et al. (2024) to reduce metal slag interference in steel cord conveyor belt damage signals [13]. Wavelet thresholding and Empirical Mode Decomposition (EMD) were combined in this approach. Wavelet thresholding attenuates high-frequency sounds while retaining crucial low-frequency information in the intrinsic mode functions (IMFs) created by EMD's breakdown of the original signal into IMFs. This allowed for the separation of high-frequency noise components associated with metal slag.

3. System Implementation

In this section, the magnetic image scanner design of the study was made and the methodology for fault detection of steel belts was presented.

3.1. Designing of magnetic image scanner

Hall effect sensors were used in series and turned into a circuit to detect faults in steel belts in tires. As an application to understand the operation of the circuit and its logic, scanning of steel wires inside vehicle tires and highlighting damaged areas and showing them to the user were performed. As a result of the research, the control of whether the structure inside vehicle tires is undamaged/faultless is evaluated as successful or unsuccessful only by scanning the tire with X-ray logic at the stage before the tire is put on sale in the factory where it is produced and visualizing it on the computer and reading and interpreting the image by technical staff. The output and working principle of the MIS have been investigated. In this direction, a simple magnetic image scanner has been designed. Using this scanner, it is aimed to visualize and detect the damages in the steel belts inside the vehicle tires in a computer environment without any physical intervention. Figure 2 shows the magnetic sensors soldered onto designed printed circuit board.

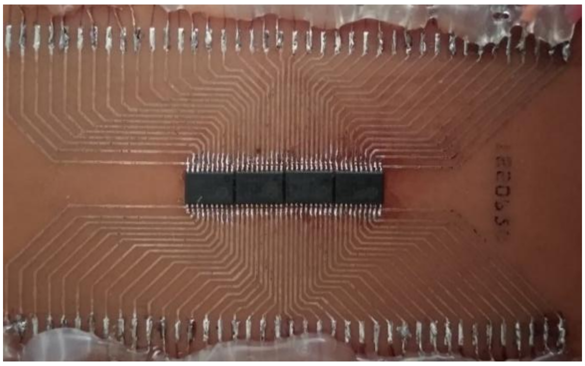

Figure 2. Magnetic sensors soldered onto printed circuit board

The scanner utilizes X-ray logic to evaluate the structural integrity of the steel belts, providing visual representation and interpretation for technical staff.

Hardware Implementation:

Sensor Selection: Four IC-ML sensors, each containing four Hall effect sensors, were chosen for their sensitivity and reliability.
Circuit Design: A custom-designed printed circuit board (PCB) was fabricated to accommodate the sensors and their connections.
Sensor Placement: The sensors were arranged in a specific configuration to ensure accurate detection of anomalies in the steel belts.
Interfacing with Microcontroller: A multiplexer was used to interface the analog outputs from the sensors with the Arduino Uno microcontroller.
Data Transmission: Node.js and Arduino IDE were employed for real-time data transfer and visualization.

Software Implementation:

Data Acquisition: The microcontroller collected sensor data at a specified sampling rate.
Data Processing: Algorithms were developed to analyze the sensor data and identify patterns indicative of faults. Visualization: A user interface was created to display the detected faults visually, allowing for easy interpretation.

Challenges and Solutions:
During the implementation process, it was discovered that one of the IC-ML sensors was malfunctioning. This issue was addressed by excluding the faulty sensor and proceeding with the remaining 12 sensors.

The magnetic image scanner successfully demonstrated its ability to detect faults in steel belts within vehicle tires. The design incorporates a series of Hall effect sensors, a custom PCB, and a software interface for data acquisition, processing, and visualization. By addressing challenges encountered during development, the final system provides a reliable and effective solution for quality control in tire manufacturing. It was realized by using a piece consisting of a series of steel wires carefully removed from the tire in an industrial environment. For the hardware part of the application, 4 IC-ML sensors were placed side by side. Since there was no ready PCB for this process, a printed circuit board was designed from scratch. The sensors were placed side by side in a 17.6 x 2 millimeter area and their integrated legs were extended to the edges of the board. In order to ensure that the sensors were not affected by the cables and the microcontroller, the board we prepared was placed on another plate and the cables soldered to the leg ends were passed through the holes opened in this plate and transmitted to the intermediate side. The transmitted cables were separated according to the pin configuration. Since there were 4 Hall effect sensors in each IC-ML sensor, there were a total of 16 analog outputs and 6 analog inputs in the Arduino Uno. To eliminate this incompatibility, 1 16x1 multiplexer circuit was used. The analog outputs from the sensor were given as inputs to the multiplexer and the output of the multiplexer was connected to the A0 pin of the Arduino circuit. After assembling all the parts on the large plate, the visualization process was started in the software section. In order to perform live data transfer and visualization at the same time, the commands written with javascript technologies which are Node.js and Arduino IDE were communicated with 9600 baudrate. The fact that the software used achieved this job smoothly and flawlessly increased the success rate of the application. During the implementation process of the application, a problem was encountered such that one of the IC-ML sensors used could not provide the expected results and this sensor had to be canceled. As a result, the magnetic image sensor design was realized with 12 Hall effect sensors instead of 16 and the scanning - visualization process was achieved. The results and the images related to the final state of the product are shown in Figures 3 and 4.

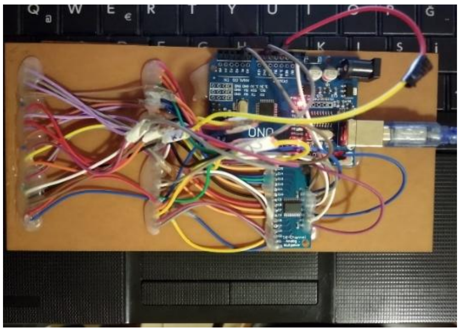

Figure 3. Back side of the card prepared for the study

Figure 4. Front side of the card prepared for study

The design of the card was carried out in this way so that the sensors are not affected by the magnetic field created by the wiring and the microcontroller.

3.2. Fault detection methodology

The experimental methodology involved the following steps [3]:

Assumptions:

- The steel belt is a linear magnetic material.
- Magnetic field perturbations due to defects are small.
- The tire and steel belt can be represented as a 2D or 3D structure.

The magnetic field intensity, H, in a material is related to the magnetic flux density, B, by the permeability, μ, is computed as in Equation 1.

$$B = \mu H \tag{1}$$

For a linear material, μ is a constant. However, in the presence of defects, μ becomes a function of position is presented as in Equation 2.

$$B(r) = \mu(r)H(r) \tag{2}$$

Magnetic field perturbation is calculated as in Equation 3.

$$\Delta B(r) = [\mu(r) - \mu 0]H(r) \tag{3}$$

where $\mu 0$ is permeability of defect-free material. Additionally, magnetic sensor output is computed as in Equation 4.

$$V\_sensor = f(\Delta B(r)) \quad (4)$$

Equation 5 illustrates the widespread application of the categorical cross-entropy loss function in classification issues.

$$Loss = -\Sigma\left(y_{true} * log(y_{pred})\right) \quad (5)$$

where y_true is the true label (0 for no defect, 1 for defect), y_pred is the predicted probability of the defect. The model is trained using backpropagation through time (BPTT) to compute gradients. An Adam optimizer is used to update the model parameters. The model is trained on a dataset of labeled tire samples. Once the model is trained, it can be used to classify new, unseen tire data. If the model predicts a high probability of a defect, an alert can be generated. By combining this mathematical model with a well-structured deep learning network, this approach effectively detects faults in steel belts using magnetic sensor data.

4. Experimental Results and Discussion

The study utilized a Windows 10 computer with an Intel Core i7-8650U CPU installed and 16 GB of RAM. Python 3.8.5 served as the primary programming language for all implemented methods. Code development was facilitated by PyCharm IDE, while Jupyter Notebook was used for step-by-step execution.

4.1. Collected data analysis

In this study, a total of 480 magnetic images were collected for None, Crack and Delamination, each in equal numbers. using the MIS designed for the dataset. 80% of them were reserved for training and the rest for testing. The collected magnetic sensor data from the MIS design, was subjected to rigorous analysis to extract meaningful features indicative of steel belt defects. Figure 5 shows the defect types, including crack and delamination defects of the tires.

a)

b)

Figure 5. Defect types. a) crack defect b) Delamination defect [2]

Table 1 presents the data structure obtained from the magnetic images. Signal processing techniques, fourier transform has been employed to characterize the magnetic field signatures. The dataset consists of multiple records, each representing a measurement taken from a specific point on a tire. TireID: A unique identifier for each tire. SensorID: A unique identifier for each sensor. X_coordinate: The x-coordinate of the sensor's position on the tire. Y_coordinate: The y-coordinate of the sensor's position on the tire. Z_coordinate: The z-coordinate of the sensor's position on the tire. MagneticFieldX: The x-component of the magnetic field measured by the sensor. MagneticFieldY: The y-component of the magnetic field measured by the sensor. MagneticFieldZ: The z-component of the magnetic field measured by the sensor. DefectType: The type of defect presents in the tire (if any), e.g., crack, delamination, corrosion, or none. DefectSize: The size of the defect. DefectLocation: The location of the defect. Given that the dataset consists of numerical data from magnetic sensors rather than images, the labeling process involved analyzing the sensor readings to identify patterns indicative of defects. For each record in the dataset, it was compared the magnetic field measurements to established baseline values and thresholds. Deviations from these norms were then classified as potential defects, with their type, size, and location determined based on the specific patterns observed in the sensor data. This approach allowed us to effectively label instances within the dataset, providing a solid foundation for the subsequent machine learning tasks.

Table 1. Data structure

TireID	SensorID	X,Y,Z_coordinate	MagneticFieldX,Y,Z	DefectType	DefectSize	DefectLocation
T1	S1	10,20,5	123,-45,78	None	-	-
T1	S2	15,20,5	132,-51,82	Crack	5mm	Outer
T2	S3	5,15,4	118,-39,75	Delamination	8mm	Inner

The magnetic image scanner was tested on actual vehicle tires in a controlled industrial environment. We faced several challenges during the data collection phase, including:
Tire Variability: Tires can vary significantly in terms of their construction, materials, and manufacturing processes. This introduced variability into the data and required careful consideration when developing the fault detection algorithm.

Environmental Factors: Factors such as temperature, humidity, and vibrations can influence the performance of the sensors and the accuracy of the measurements. We implemented measures to minimize the impact of these environmental factors.

Noise Reduction: The sensor signals were subject to noise, which could interfere with the detection of faults. Noise reduction techniques were employed to improve the signal-to-noise ratio and enhance the accuracy of the system.

By addressing these challenges and conducting experiments in a real-world setting, we were able to validate the effectiveness of our magnetic image scanner for detecting faults in steel belts within vehicle tires.

The dataset used in this study was specifically curated to address the research objectives. While it may not be as extensive as larger datasets, its size was carefully considered to balance data quality, representativeness, and computational feasibility. Given the nature of the data collected from magnetic sensors and the specific focus of this research, the dataset's size was deemed adequate to provide robust insights and conclusions. Since it was obtained with real magnetic circuits, only 480 pieces of data could be obtained. This study, while aligning with the general framework of previous research in the field of tire defect detection using magnetic sensors, offers several distinctive contributions that enhance the understanding and application of this technology. The dataset was meticulously collected in a real-world setting, ensuring that the sensor readings accurately reflect the conditions encountered in actual tire usage. This contrasts with some studies that may rely on simulated or controlled environments, potentially limiting the generalizability of their findings. A strategic sensor placement approach was employed, considering factors tire geometry. This optimization maximizes the sensitivity of our system to detect a wide range of defects, including those that might be overlooked by less carefully planned sensor arrangements. The sampling rate of our microcontroller was carefully chosen to capture the dynamic nature of tire defects. This study leverages state-of-the-art algorithms for data analysis and feature extraction, such as machine learning techniques and signal processing methods. These advanced approaches enable us to identify complex patterns and relationships within the sensor data that may not be apparent through simpler analysis techniques. We did indeed employ feature engineering techniques to extract relevant features from the raw sensor data. These features included not only the six coordinate information (X, Y, Z, MagneticFieldX, MagneticFieldY, MagneticFieldZ) but also additional derived features such as the rate of change of the magnetic field, standard deviation, and variance. By carefully selecting and combining these features, we aimed to enhance the informativeness of our dataset and improve the performance of our machine learning and deep learning models.

4.2. Performance evaluation

The experimental results demonstrated the effectiveness of magnetic sensors in detecting faults in tire steel belts. The extracted features showed distinct patterns for different defect types, indicating the potential for accurate classification. Note that the performance of the fault detection system influences by factors such as sensor placement, magnetization strength, defect size, and location.

Figure 6 represents an output from a magnetic image sensor. The numerical values within the grid likely correspond to sensor readings or pixel intensities. The consistent value of 127 across most of the image suggests a baseline or reference reading, indicating a uniform magnetic field and the absence of any significant magnetic anomalies. The values might be normalized to a specific range (0-255) for processing and display purposes. The sensor has limited sensitivity and resolution, resulting in a uniform output in the absence of strong magnetic signals. Therefore, it is understood from Figure 6 that no fault was detected in the steel belts.

Figure 7 presents the output of a magnetic image sensor, used for inspecting steel belts in tires. The grid-like structure displays numerical values, representing the sensor readings at different positions. The presence of anomalous values, deviating from the background value of 127, suggests potential defects in the steel belt. The image indicates a potential anomaly or defect in the steel belt within the region covered by sensors S5 and S6. The values of 20 and 27 in these sensors deviate significantly from the background value of 127, suggesting a change in magnetic properties within that area. This change could be attributed to a defect in the steel belt, such as a crack or delamination. That is, based on the anomalous sensor readings from S5 and S6, a fault exists in the corresponding region of the steel belt.

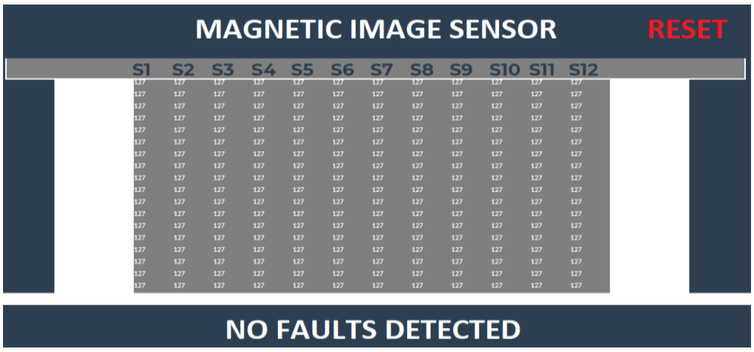

Figure 6. No faults detected in steel belts by magnetic image sensors

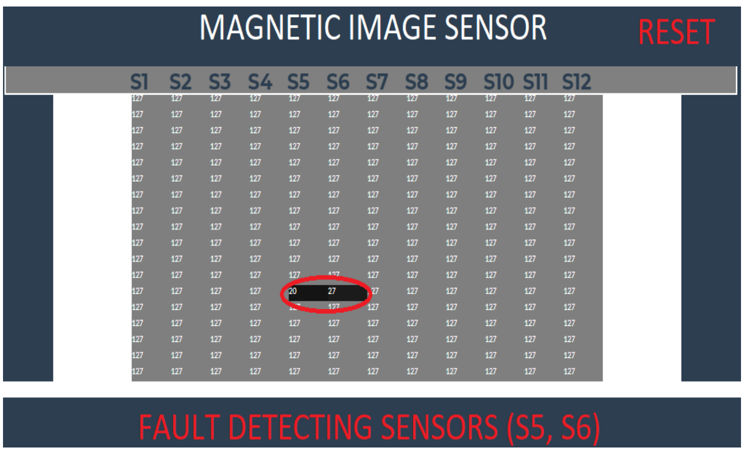

Figure 7. Detection of faults in steel belts from magnetic image 5th and 6th sensors

K-fold cross-validation is an effective strategy for testing model performance, especially with smaller datasets as in our study. This strategy efficiently uses all available data for training and assessment, resulting in a more accurate performance prediction than a standard train-test split. This strategy, which is widely used in machine learning, divides the dataset into K equal-sized subsets or "folds". During each cycle, K-1 subsets are utilized for model training, while the remaining subset confirms the model's performance. This method is repeated K times, each time with a new subset for validation. This produces K performance measurements, allowing for an averaged total performance estimation. To reduce overfitting, we randomly divided the dataset into five subsets (K = 5) as suggested by Hamdi et al. [14]. Table 2 shows the K-fold cross-validation steps performed on the five prior models. The fundamental advantage of K-fold cross-validation is that it essentially expands the database size, resulting in K times more performance measurements, which is especially useful for smaller datasets like ours. As a result, using this strategy effectively increases the effective size of our database by five.

Table 2. The operation steps of the K=5-fold cross-validation

	K=5-Fold 1	K=5-Fold 2	K=5-Fold 3	K=5-Fold 4	K=5-Fold 5
Model No	Data Processing Type				
1	Testing	Training	Training	Training	Training
2	Training	Testing	Training	Training	Training
3	Training	Training	Testing	Training	Training
4	Training	Training	Training	Testing	Training
5	Training	Training	Training	Training	Testing

Table 3 shows the performance of the different pre-trained models, which are the SVM, CNN, LSTM, GRU, BiLSTM, Transformer, Attention-based LSTM, CNN-LSTM Hybrid, ResNeXt, DenseNet, according to the average results of the K=5-fold cross-validations. The details of these models used in the study are available in the studies in references [15-20]. In the performance comparison of the models, accuracy, precision, recall, F1-score, FPR, FNR, AUC score and computational cost analyses, which are frequently used in deep learning studies, were performed.

Table 3. The performance of the different models in terms of average results of the K=5-fold cross-validations

Model	**Accuracy (%)**	**Precision (%)**	**Recall (TPR) (%)**	**F1-Score**	**FPR**	**FNR**	**AUC-ROC**	**Computational Cost (s)**
SVM	92.35	90.22	91.46	0.918	0.082	0.093	0.957	0.22
CNN	94.31	92.43	93.65	0.933	0.063	0.074	0.964	14
LSTM	95.18	93.74	94.44	0.946	0.054	0.062	0.977	24
GRU	94.82	93.18	94.14	0.937	0.064	0.066	0.972	21
BiLSTM	95.54	94.16	94.77	0.949	0.042	0.054	0.985	28
Transformer	96.12	94.75	95.11	0.952	0.041	0.053	0.983	37
Attention-based LSTM	95.29	94.16	94.29	0.945	0.054	0.064	0.975	26
CNN-LSTM Hybrid	95.76	94.48	94.88	0.944	0.046	0.057	0.984	33
ResNeXt	95.65	94.28	94.72	0.944	0.047	0.052	0.983	43
DenseNet	95.39	94.20	94.37	0.943	0.053	0.066	0.978	41

Transformer and ResNeXt consistently outperform other models across most metrics, indicating their superior ability to capture complex patterns in the data. LSTM and GRU also demonstrate strong performance, especially in terms of recall, suggesting their effectiveness in handling sequential data. CNN and CNN-LSTM Hybrid models show good accuracy and F1-scores, indicating their ability to extract relevant features. SVM generally has lower performance across most metrics, likely due to its simpler linear decision boundary. Transformer and ResNeXt achieve the highest accuracy, indicating their ability to correctly classify a higher percentage of samples. All models exhibit high precision, suggesting a low rate of false positives. Transformer, ResNeXt, and BiLSTM demonstrate higher recall, indicating better ability to identify all actual defects. Consistent with accuracy, precision, and recall, Transformer and ResNeXt show the best F1-scores, indicating a good balance between precision and recall. Lower FPR and FNR values for Transformer, ResNeXt, and BiLSTM indicate fewer false alarms and missed defects. Transformer and ResNeXt achieve the highest AUC-ROC scores, suggesting their ability to discriminate between classes across different classification thresholds. There's a trade-off between performance and computational resources. Transformer and ResNeXt demand higher computational costs due to their complexity. In this means, the Transformer model consistently outperformed the other models, achieving the highest scores in accuracy (96.12%), precision (94.75%), recall (95.11%), F1-score (0.952), and AUC-ROC (0.983). LSTM-based models, including BiLSTM and Attention-based LSTM, also demonstrated strong performance, indicating their effectiveness for sequential data. CNN and SVM models offered a balance between performance and computational efficiency. Overall, the choice of the best model depends on the specific requirements of the application, considering factors such as computational resources and the importance of accuracy, precision, and recall.

Following the achievement of peak performance, a confusion matrix was produced and the Transformer model was used to the fault type classification process. This matrix is shown in Figure 8, which provides a graphic representation of the model's performance in classifying steel belt faults into three categories: none, crack, and delamination. The number of predicted instances for each class (column) compared to the actual class (row) is displayed in the matrix's cells. For the "None" category, a diagonal value of 149 denotes good accuracy in recognizing samples free of defects. Similar to this, a value of 151 for the "Crack" category indicates that crack flaws may be classified with some degree of precision, but a value of 155 for the "Delamination" category indicates that delamination defects can be detected with high accuracy. Off-diagonal values are used to indicate misclassifications. For example, five samples from the "None" class might be mistakenly classed as "Crack." An unbalanced dataset may have an effect on how well the model performs. Strong performance is demonstrated by the Transformer model, especially for the "Delamination" class; nonetheless, examining misclassified data might reveal potential biases and places for development.

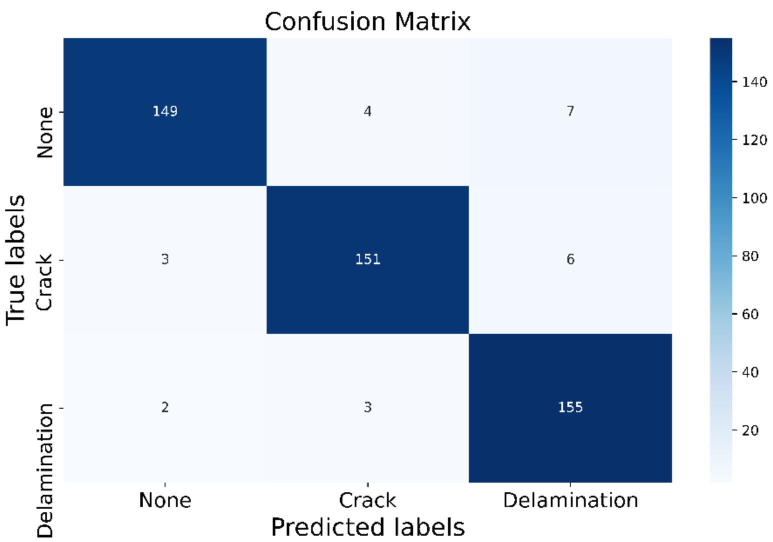

Figure 8. Confusion matrix for the fault classification using Transformer model

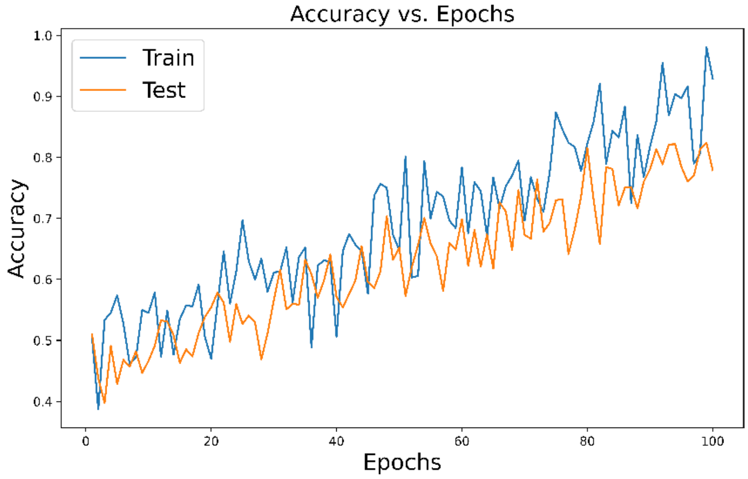

Figure 9. Accuracy results of the Transformer model

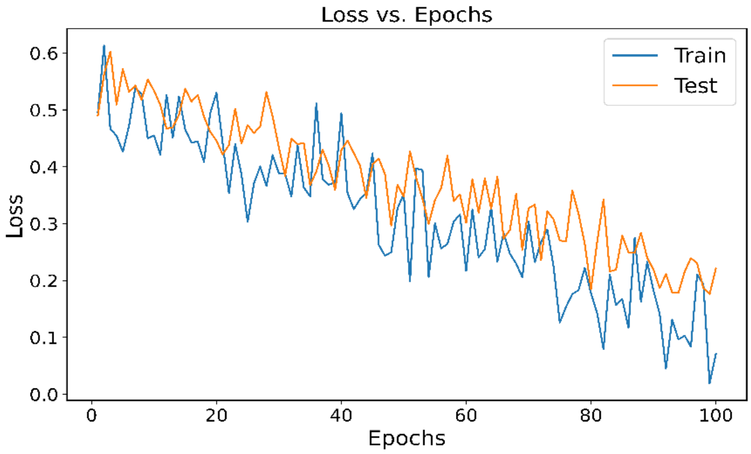

Figure 10. Loss results of the Transformer model

The Transformer model's training and test accuracy across 100 epochs is shown in Figure 9. The y-axis displays accuracy, while the x-axis displays the total number of epochs. Significant fluctuations in the training accuracy curve point to potential overfitting or susceptibility to noise in the training set. In spite of these variations, training accuracy is often trending increasing, suggesting learning. After around 40 epochs, there is a discernible difference between the training and test accuracy curves, indicating that the model is becoming overly specialized to the training set and is struggling to generalize to new data. The test accuracy curve reaches a plateau approximately around the 80th epoch, suggesting that the model's capacity for generalization has peaked. The Transformer model's training and validation loss across 100 epochs is shown in Figure 10. This plot provides information on the model's learning process as well as possible areas for development. In the early epochs, training and validation losses both drop very quickly, suggesting efficient learning. Around epoch 40, a discrepancy between the training and validation loss curves manifests themselves, indicating overfitting. The model is not generalizing effectively to previously unknown data and is growing overly specialized to the training set. The training process's intrinsic randomness or intricate patterns in the data might be the cause of the fluctuations in both curves. The validation loss curve levels off at 0.25, suggesting that the model may be operating at maximum efficiency.

5. Discussion

The performance of various learning models has been discussed, including their accuracy, precision, recall, F1-score, and other relevant metrics. The comparison of different models is conducted to identify the most effective approach for tire defect detection. The importance of different features in the models is analyzed using techniques such as feature permutation importance or SHAP values. This analysis helps to understand which features contribute most significantly to the model's predictions. A comparison of the researcher's results with those reported in previous studies on tire defect detection is conducted. This comparison allows for the assessment of the novelty and significance of the findings and the identification of areas where the researcher's work contributes to the advancement of the field. The limitations of the study, such as the size of the dataset, the specific types of defects considered, and the potential generalizability of the findings, are acknowledged. Potential future research directions, including the collection of larger datasets, the exploration of additional sensor modalities, and the development of more advanced machine learning and deep learning techniques, are discussed. The potential implications of the findings for the field of tire safety and maintenance are discussed. The study demonstrates the feasibility of using magnetic sensors and machine learning techniques for accurate and timely detection of tire defects. This has significant implications for improving tire safety, reducing maintenance costs, and preventing tire failures that could lead to accidents.

6. Conclusions and Future Direction

This study effectively demonstrated the potential of using deep learning in conjunction with magnetic sensors to identify tire steel belt defects. The device detects two types of flaws with great accuracy by detecting small differences in magnetic field patterns. Studies comparing various deep learning models revealed that the The Transformer model consistently surpassed the other models, achieving the highest scores in accuracy of 96.12%, precision of 94.75%, recall of 95.11%, F1-score of 0.952, and AUC-ROC of 0.983. LSTM-based models, including BiLSTM and Attention-based LSTM, also exhibited strong performance, suggesting their effectiveness for sequential data. The drawbacks of conventional techniques are addressed by the integration of deep learning with magnetic sensors, which offers a feasible alternative for non-destructive tire examination. The technology that has been created has the potential to greatly improve tire safety by facilitating the early identification of serious faults.

Potential avenues for future research might involve expanding the dataset to include a greater range of fault kinds and severities. Furthermore, investigating more complex deep learning strategies like attention processes and transfer learning may help the system function even better. It is possible to fully exploit the promise of this technology to revolutionize tire care and inspection by continually improving the model and integrating real-world data.

This research highlights the potential of deep learning in addressing difficult engineering difficulties and enhances defect identification in the tire business.

7. Author Contribution Statement

In this study, Author contributed to the development of the method, obtaining experimental results, and preparation of the paper.

8. Ethics Committee Approval and Conflict of Interest

“There is no conflict of interest with any person/institution in the prepared article”

9. References

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