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Abstract:

Feed pellets, which hold a significant position in various industries, utilize gearboxes for the proper gear ratio required for pellet making. Moreover, these gearboxes are not only vital for pellet machines but for other machines as well in different industries. In this regard, their timely maintenance is a significant challenge that can be catered to by the use of modern techniques like CM and SHM. This study aims to use ML models for predictive maintenance. A multi-sensor technique comprising an acoustic and vibration sensor was used for a two-stage gearbox. There were three scenarios used in the current study, which were healthy, edge broken, and broken half tooth mounted on an intermediate shaft. A gearbox with a combined ratio of 5.122 was used. The ADXL335 accelerometer and a MAX9814 microphone were used for extracting data. This data acted as input to MATLAB, which was then used for ML. All the built-in machine learning models in MATLAB were trained. The ML model named Fine Tree gave an initial accuracy of 48.8%. Then, by training the ML models by features instead of all the compiled data and modifying the code to detect data leakage, leak-free accuracy came out to be 63.98% and Fine Tree as 91.8%. The findings support that successful machine learning for predictive maintenance was done on the data extracted from multiple sensors for a 2-stage gearbox, and some future recommendations were also discussed.

Keywords Machine Learning, Multi-sensor, Two-stage spur gearbox, Structural Health Monitoring (SHM), Fine Tree model, leak-free accuracy

Introduction:

Feed pellets are widely used in the agriculture and poultry sectors because they have comprehensive nutritional value, digestibility, and stability [1]. Similarly, pellet machines are used to make fish feed in the form of pellets [2]. In wind turbines and other industrial equipment, rotary equipment plays a vital role. These rotary machines comprise bearings, shafts, and gears. Due to applications in harsh environments, they often fail and cause downtime and various other losses [3]. Despite these applications, gears are also a crucial part of many sectors such as aviation, railway, the automotive sector, and many more. Moreover, a defect in them causes disturbance in the entire system. Thus, early fault diagnosis and condition monitoring hold a pivotal role in the transportation sector from a reliability and safety perspective [4]. These issues require more advanced materials and real-time monitoring to improve reliability. In this regard, the Structural Health Monitoring (SHM) technique is commonly used to find faults using acoustic and vibration sensors [5]. Pellet machines, when operated, face forces at approximately the natural frequency [2]. Also, Condition Monitoring (CM) has gained significant importance in industrial processes. The main underlying concept of CM is to prevent failure by obtaining data on various parameters of a component [6]. Gearboxes are the most used transmission components. This is why many researchers are interested in gear dynamics and behaviors [7]. The gearbox holds a significant position in the feed pellets and biomass production system. These gearboxes affect the torque, speed, and efficiency of the process. Thus, spur gears are usually used in low-speed, high-torque applications, commonly in small-scale pelletizing processes due to their simplicity and efficiency. Commonly used gear ratios in gearboxes for pelletizing processes are 1:5 to 1:20, while some using planetary gearboxes achieve a gear ratio of 1:1000 [8].

Research was conducted on the pitch bearings of wind turbines. In that research, researchers proposed a new methodology for fault diagnosis. The method proposed was named Bayesian augmented temporal convolutional networks (BATCN). This method uses deep learning techniques to learn the intrinsic features of fault signals to guarantee the extraction of non-stationary fault signals. The results showed that this technique has good accuracy at slow-speed moving blades, even better than the well-known Spectral Kurtosis (SK) technique [9]. Y. Tong *et al.* studied design strategies for materials, data-acquisition methods, and safety assessment techniques. They discussed the data acquisition and transmission technologies and concluded that vibration sensors provide real-time structural monitoring, acoustic sensors provide detection of internal micro-cracks, while strain measurement focuses on performance assessment [5]. K. Wu, Z. Li, C. Chen, Z. Song, and J. Wu researched using the MBCAN model for fault diagnosis using 6 vibration signals on a gearbox. Gear and bearings with different defects were used to analyze the gearbox. They concluded that analysis using the MBCAN method is more accurate and robust than previously presented methods [3]. Bai *et al.* analyzed scrapped ring die of a pellet machine. Since the ring die was rusty, it failed before the designed service life. They concluded that the entrance to the ring die hole was the severely worn position, further confirmed by morphological analysis of the worn surface. Surface small pits deteriorate the mechanical properties and wear resistance, promoting fatigue failure. The major wear mechanism at the die ring entrance is a combination of third-body abrasive wear, fatigue, and electrochemical corrosion [1]. Lostari *et al.* modeled and simulated the gearbox of the pellet machine. They found that displacement vibration response on the gearbox of the pellet engine system produced an RMS value of 0.7277 m, an initial peak point of 1.086 m, and a valley point of 1.048 m. They also concluded that the worm gear in the gearbox had a displacement vibration response of 1.0585m and an acceleration response of 6.8485 m/s^2 [2]. Qu *et al.* used fiber Bragg grating (FBG) and piezoelectric strain sensors for dynamic gear analysis. A single-stage spur gearbox was used for the analysis with a gear ratio of 1.8 and a module of 3. They found that FBG and piezoelectric sensors could effectively reflect the dynamic transition of tooth root stress and record the details of gear dynamic strain. Along with that, they concluded that extended tooth contact greatly affects the tooth root strains. Also, tooth pitting affects gear strain, resulting in abnormal vibration signals [7].

Regarding the vast research in the domain of Condition monitoring of gearboxes for fault diagnosis, V. Sharma and A. Parey encapsulated and researched the research in the past in this regard. They found that various indicators were used to find different faults leading to complete failure of the gearboxes. The summary of which is included in their paper. However, they suggested that research is already done on the individual components of the gearbox, whereas in reality this is not the case. Also, they discussed that most research is on stationary speeds whereas variable speed is still an untapped area. Moreover, most of the analysis is done for gearboxes of limited machinery such as helicopters, rolling mills, or wind turbines. At last, they suggested use of various indicators simultaneously to predict failures with more than one defect [10]. Similarly, another problem in these types of monitoring is the unavailability of sufficient data for the training of deep learning (DL) model. Thus, S. R. Saufi *et al.* proposed DL model based on stacked sparse autoencoder (SSAE) model was used for fault diagnosis system, that was developed based on time-frequency image pattern recognition. As a result, results of good accuracy were achieved with 100% and 99% diagnosis performance on 2 wind turbine gearboxes dataset [11]. Similarly, Asif *et al.* researched Structural Health Monitoring of Spur Gears using acoustic and vibration sensors. Data from individual sensors as well as fused data was used for model training. A total of 60,060 points were used for supervised machine learning of fused data. The setup in the paper shows that a single-stage gearbox was made for the analysis. Moreover, analysis was done for 1 healthy and 4 defective, mainly comprising broken and cracked gears at various speeds. Finally, it was concluded that fused data yielded 95.0% accuracy using the Fine KNN model as the best analysis model [12]. Similarly, D. M. Bourdalos and J.S. Sakellariou researched gear fault analysis using a vibration sensor on a single-stage gearbox along with a tachometer, which was used to measure operating conditions. This vibration signal was a single tri-axial accelerometer placed on the ball bearing housing of the secondary shaft. It was one of the conclusions of the research that ML methodology achieved 95.4% overall accuracy for fault detection and 91.6% for fault severity characterization [13]. F. Karpat *et al.* collected data for healthy and four different levels of cracked spur gears used in the railway sector (25-50-75-100%) at different speeds via an accelerometer. This data was collected via MATLAB and then given as input to machine learning algorithms. They concluded that AI-based methods are suitable and adaptable for fault detection in rail-based transportation systems [4]. A two-stage reducer of spur gear was analyzed by vibration signals only. It was found that the multi-unit fusion learning method achieved high accuracy for fault detection [14]. Similarly, a two-stage spur gearbox was used along with other components, such as a planetary gearbox, to model the gearbox of a wind turbine. Noise signal was only used on the entire system for analysis and training of the machine learning model for different speeds and different defects in the gear. It was found that the machine learning model achieved high accuracy with a noisy signal only [15]. Moreover, a study investigated a two-stage spur gearbox using multiple current sensors to validate the effectiveness of the proposed ML model based on a 2-D convolutional neural network [16]. Moreover, a study was conducted on a two-stage wind turbine gearbox with a combined gear ratio of 20.45:1. The defects were composite in nature, such that different defects were created on different components of the gearbox such as high-speed bearing failure and intermediate speed pinion gear chipping, and many more. A total of 5 such composite cases were taken, and data were generated by an audio microphone, triaxial accelerometer, torque sensor, and rotational speed sensor. This data was fed to the proposed hybrid fault diagnosis framework named CEKNN, which is a combination of Convolutional Extension Neural Network (CENN) and K-Nearest Neighbor (KNN) model. The study concluded that the proposed framework achieved accuracy of 97.1% [17].

Various literature can be found on the fault diagnosis of gearboxes. Some of the research is conducted using multi-sensor systems employing vibration and acoustic sensors. While some others have used a single sensor. Similarly, some researchers have used machine learning, and some have not. Also, at constant and variable speeds, research is done. Thus, in a nutshell, it can be easily said that research on fault diagnosis of gearboxes has been done considering various factors: number of and type of sensors, speed, machine learning, type of gearboxes, and gears used in that gearbox. Commonly, single-stage gearboxes are used, consisting primarily of spur or helical gears. Some have done 2-stage gearboxes but haven't filled the gap for fault diagnosis. This creates a research gap for analyzing a 2-stage gearbox composed of spur gears using machine learning trained on multi-sensor data. The research on gearbox failure due to gears is necessary because around 26% of gearbox failures are caused by gears. Although these defected gears are the result of various defects of different components of the gearbox but this 26% are the real cause of complete failure [18]. Thus, this research revolves around the fault diagnosis of a 2-stage spur gearbox using different sensors, such as vibration and acoustic, on different cases of gears, to feed data to a machine learning model.

Design Methodology:

Initially, CAD modelling was done, which then proceeded to the manufacturing phase. After manufacturing was completed using traditional workshop machines. The components were brought together for the assembly phase. Assembly was done, ensuring proper gear meshing. Acoustic and Vibration sensors were employed for data acquisition. And after data acquisition, MATLAB was used for machine learning. The schematic is shown in Figure 1.

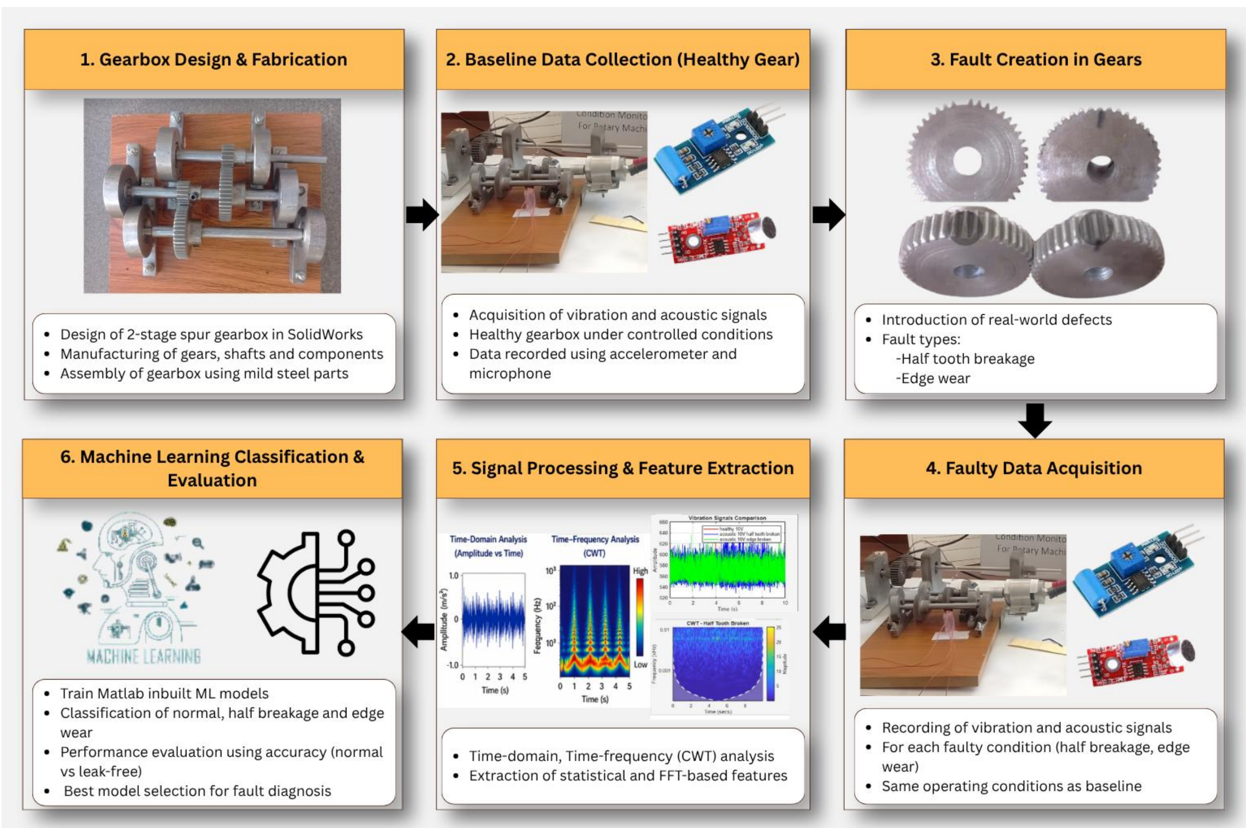

Figure 1: Schematic of methodology

Fabrication and Experimental Testing:

The complete 3D model of the 2-stage gearbox was designed in SolidWorks. The 3D model includes all the essential parameters, such as the module and the number of teeth on each gear. After designing a 3D model, the gears were manufactured in a conventional workshop using a milling machine. The material of the gear was chosen to be mild steel. A pinion of module 1 with 19 teeth and a gear of module 1 with 43 teeth were selected as gear parameters. These were used in a 2-stage gearbox at each stage to achieve the required speed reduction with a combined gearbox ratio of 5.122.

Then three shafts of 10mm diameter were manufactured in a workshop using a lathe machine. 1st shaft that transmits power from the motor to the first stage gears was approximately 140mm long, the input shaft, 2nd shaft that connects the first stage gears to the second stage gears, and the intermediate shaft were 150mm long, and the 3rd output shaft was approximately 180mm long. Ball bearings of the 607 series were used for rotating shafts, which were sourced from an external source to make sure reliability and standardization. Once all components were manufactured, it was then assembled carefully to ensure proper alignment and meshing of gears.

First, the assembled gearbox was run in its normal, healthy state to record the baseline acoustic and vibration readings. After getting this initial data, the gearbox was disassembled to create specific faults in the gears, like the real-world defects found in industries. Two types of gear defects were made for testing. For the first defect, partial tooth breakage, a half tooth was broken, in which a section of a single tooth was removed using a flat hand file. For the second defect, edge wear, about half the thickness of the selected teeth was filed away using the same hand file, named edge broken. This was done to copy the severe wear patterns caused by misalignment.

When the defective gears were ready, the gearbox was reassembled for testing. First, the gear with a broken tooth was installed. The gearbox was run under the exact same conditions as the baseline test, and the new acoustic and vibration readings were recorded. After that, the gearbox was reopened to change the broken gear with the edge wear defect gear, assembled it back and started the input motor to get the readings. This step-by-step process made sure that the specific noise and vibration of each defect could be clearly recorded and compared to the healthy gears. The gears which were damaged and healthy under study were mounted on th intermediate shaft.

Figure 2: Two defective gears with Edge Broken, left side, and Half Tooth Broken, on the right side

Results and Discussion:

The graphs between Amplitude and Time show a clear distinction between healthy and damaged tooth gearboxes, which was made using simple MATLAB code. In a healthy gearbox, there are no sudden but meager spikes in the amplitude throughout the time span. This shows that the gear is operating under normal conditions. However, in the case of Faulty gears, we got sharp and sudden spikes in the amplitude. These spikes represent the irregular contact, vibration burst, and sudden impact. Moreover, Faulty gears had a high amplitude relative to the damaged tooth, which is clear from Figure 3. These clear spikes and high amplitude help to distinguish the model between healthy and faulty gear.

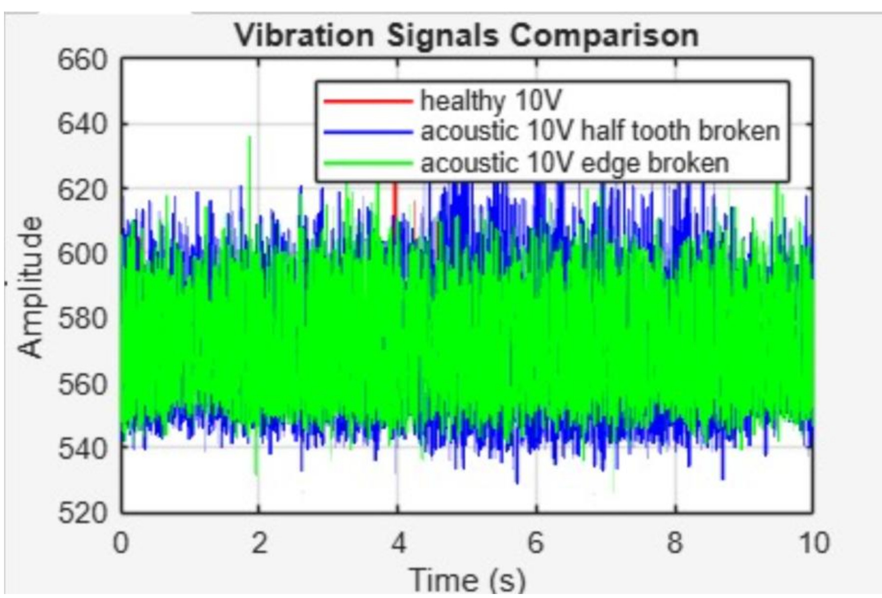

Figure 3: Amplitude vs Time Graph considering all cases at 10V

To increase the understanding of these signals, Continuous Wavelet Transform (CWT) analysis was performed, which was made using simple MATLAB code. This analysis shows how the energy of signals is distributed in the frequency and time domains. The CWT of the healthy gear shows a low energy level across the frequency spectrum, showing stable patterns without abrupt disturbance. However, in the faulty signals, there is an increase in energy in higher frequency regions because of the presence of sudden impacts and irregular vibrations due to the defects. Particularly in Half tooth broken conditions show more severely high in energy shows more intense and concentrated energy, suggesting more severe damage to the tooth. The variation of energy over time was transient and not easy to get on an amplitude-time graph. CWT provides deeper insight into faulty characteristics.

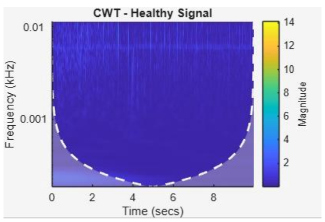

Figure 4: CWT of healthy gear

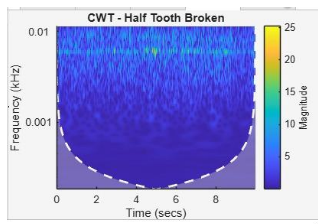

Figure 5: CWT of Half Tooth Broken Gear

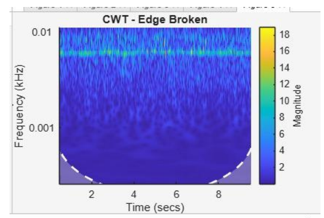

Figure 6: CWT of Edge Broken Gear

The MATLAB code that was developed implements a complete machine learning pipeline for gear fault classification. This code classifies using vibration and acoustic signals. Initially, raw data corresponding to three conditions: Healthy, Half Tooth Broken, and Edge Broken were loaded from separate .mat files. Each signal was then distributed into 1000 samples that were equally distributed, ensuring that there was sufficient data for machine learning. Also, a unique source identifier is assigned to each recorded original signal for leakage-free validation. Then, from each separate signal, a set of statistical and frequency-domain features was extracted, such as mean, standard deviation, RMS, peak values, skewness, kurtosis, and frequency band energies obtained via Fast Fourier Transform (FFT). These features were input to the classification stage. The dataset was initially evaluated using a conventional random split, where 80% of the data was split to be used for training and 20% for testing. A weighted k-nearest neighbor (KNN) classifier (k=5) was implemented manually in the code without using external toolboxes, where Euclidean distance is used, and closer neighbors are given higher importance. A classification learner was used to train models with a cross-validation set to 10 for each trial. Also, a leak-free technique was employed to get the results. Finally, classification accuracy was calculated for both evaluation techniques, allowing a comparison between conventional and leakage-free results.

For the initial case, when the data was trained, the data Set variable was set to all the data compiled as a result of the code that was executed instead of the features. So, the results showed a low accuracy of 48.8% by the most accurate model in our case, which was Fine Tree, as shown in Figures 7 and 8.

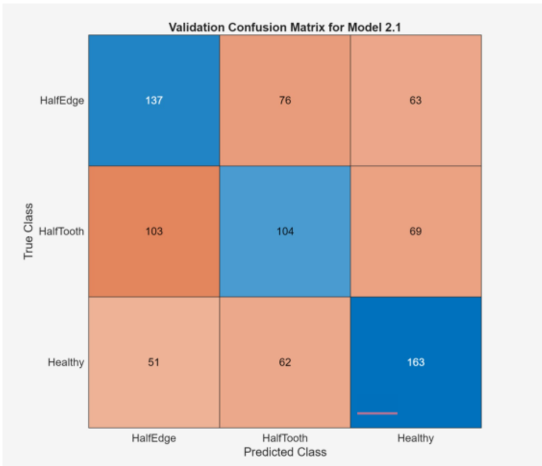

Figure 6: Initial data ML confusion matrix

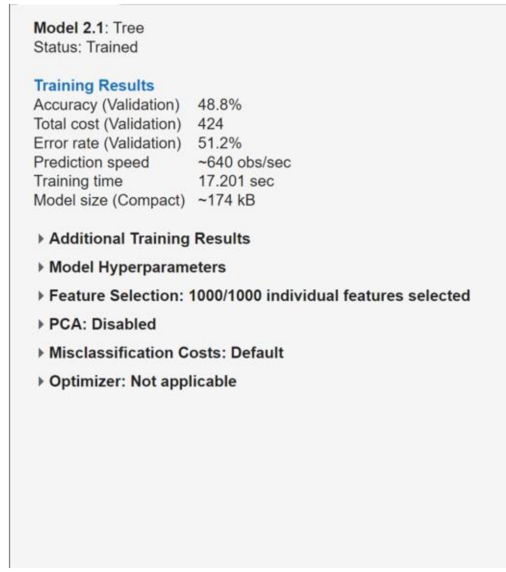

Figure 7: Initial Data result of the most accurate model

In another trial, the Confusion Matrix shown in Figure 9 shows that the model performed well and classified correctly along the diagonal. In this matrix, we have the highest accuracy of (259 Correct) for healthy signals, while half tooth and half edge represent the good classifications with minor misclassifications between them.

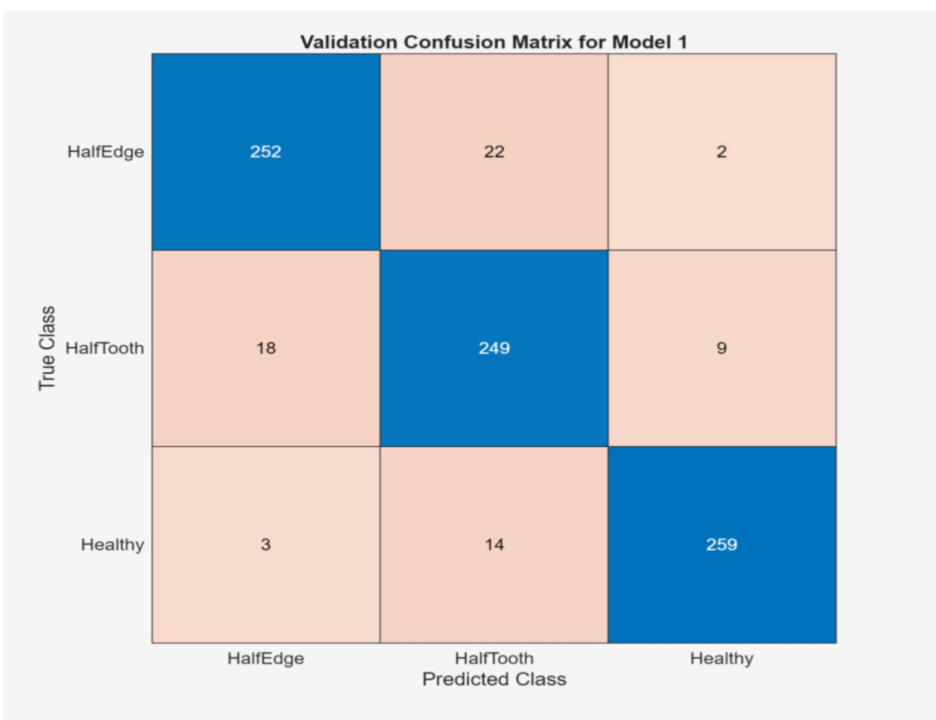

Figure 8: Confusion Matrix after changing parameters and data cleaning

The Results of the model, as shown in Figure 10, which we trained after setting the data Set variable to Features, show strong performance reliability, indicating that it has learned the patterns in the data. We used many models, but the picture shows the model with the highest accuracy, just to make it reliable. The most accurate results were provided by the Fine Tree model, providing an accuracy of 91.8% as shown in Figure 10. This means that there is no significant mismatch between our trained model and the actual results, which shows that our method and approach were right. Our model is reliable, making it usable for further fault detection. This accuracy might be after data leakage. Also, to achieve a better, more realistic performance estimate, a second evaluation was performed that consisted of a leakage-free approach, in which all segments from a single recording were explicitly assigned to either the training or testing set, depending upon their source IDs. This ensured segregation and independence between training and testing data.

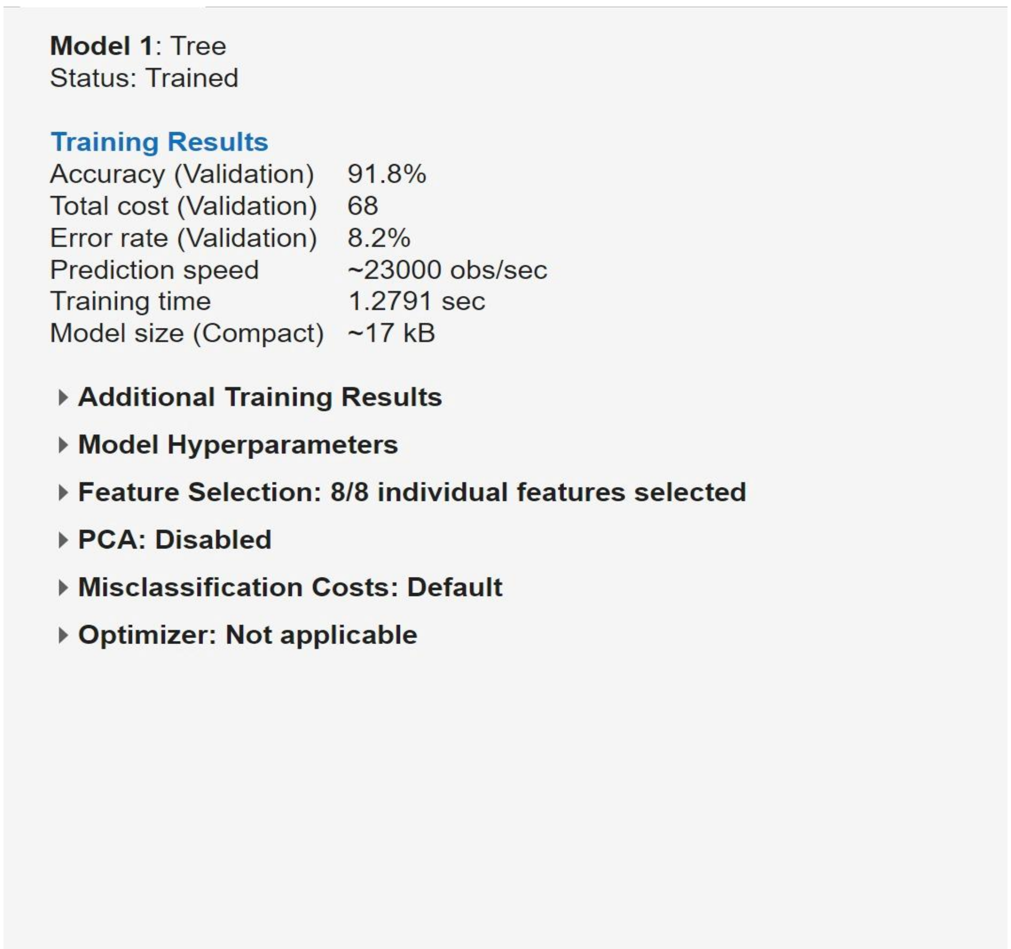

Figure 9: Results of the most accurate model after changing parameters and data cleaning

So, the MATLAB command window was used for checking accuracy after a leak-free segment of code was added to the main code. Figure 11 shows the accuracy and leak-free accuracy, that comes out to be 72.29% and 63.98%, respectively, calculated by MATLAB.

Figure 10: Command Window results

Conclusion:

The project achieved the design, fabrication, and analysis of a two-stage spur gear, considering appropriate design and manufacturing processes, which consist of spur gears, shafts, and bearings. The model was tested under healthy and defective conditions, which included two realistic gear faults, which were partial tooth breakage and edge wear, which were intentionally induced to depict real-life industrial faults. Experimental results demonstrated a clear distinction between healthy and faulty gears, as sudden impact loads and inappropriate meshing caused the system to produce irregular and high-amplitude spikes in the Time-Domain Signal analysis, whereas healthy gears gave stable vibration patterns. Continuous Wavelet Transform (CWT) analysis provided further insight into the time-frequency characteristics of the signal, showing higher localized energy concentrations in faulty gears, particularly for the broken tooth case. Advanced Signal Processing was effectively utilized for identifying transient and non-stationary fault signatures. The machine learning model trained on gathered multi-sensor data showed strong classification performance, as shown in the Confusion Matrix in Figure 10, as most predictions were correctly classified along the diagonal. This showed the reliability of the model in distinguishing between healthy and faulty gear conditions with only minor misclassification between similar gear defects. It validates the success of employing combined vibration and acoustic sensors along with data-driven techniques for Predictive Maintenance operations. The study still admits certain limitations in its practice despite these achievements, as two defects were considered in a controlled laboratory environment, which cannot incorporate the complexity of real-world industrial conditions. Limitations of the dataset and testing under relatively constant operating conditions did not consider the extensive variation of load over longer service periods. In the future, there can be further enhancements in the model, which include considering a wide range of defects like shaft misalignment, bearing defects, and lubrication-related failures along with study of multi-stage gearboxes. Real-time monitoring systems, such as embedded sensors, and IoT-based platforms implementation can provide continuous condition tracking in practical applications. Moreover, future work also includes leak-free machine learning by enhanced preprocessing, splitting of data into train and test data, and many more such practices. In conclusion, the project demonstrates successful integration of mechanical design, experimental testing, signal processing, and machine learning for gearbox fault diagnosis. The developed system highlights the potential of multi-sensor-based condition monitoring as a reliable and developed approach for early fault detection, enhanced system reliability, and reduced maintenance costs.

Bibliography:

[1] H. Bai, B. Zheng, W. Li, and X. Tu, "Failure analysis of ring die of a feed pellet machine," *China Foundry*, vol. 17, no. 2, pp. 167–172, Mar. 2020, doi: 10.1007/s41230-020-9104-8.

[2] A. Lostari, Susastro, and T. Machfuroh, "View of MODELING AND VIBRATION RESPONSE ANALYSIS OF PELLET MACHINE GRINDER AND GEARBOX." Accessed: Feb. 21, 2026. [Online]. Available: https://jurnal.umj.ac.id/index.php/sintek/article/view/6281/5042

[3] K. Wu, Z. Li, C. Chen, Z. Song, and J. Wu, "Multi-branch convolutional attention network for multi-sensor feature fusion in intelligent fault diagnosis of rotating machinery," *Qual. Eng.*, vol. 36, no. 3, pp. 609–623, Jul. 2024, doi: 10.1080/08982112.2023.2257762.

[4] F. Karpat, A. E. Dirik, O. Dogan, O. C. Kalay, and A. Et., "A Novel AI-Based Method for Spur Gear Early Fault Diagnosis in Railway Gearboxes," *2020 Innov. Intell. Syst. Appl. Conf. ASYU*, 2020, doi: 10.1109/ASYU50717.2020.9259819.

[5] Y. Tong *et al.*, "Materials Design and Structural Health Monitoring of Horizontal Axis Offshore Wind Turbines: A State-of-the-Art Review," *Materials*, vol. 18, no. 2, Jan. 2025, doi: 10.3390/ma18020329.

[6] H. W. Qin, F. C. Cao, Q. Y. Fan, and M. J. Aishan, "Use of AE Testing Data for Condition Monitoring in Wind Turbine Gearbox," *Adv. Mater. Res.*, vol. 1070–1072, pp. 1893–1897, 2015, doi: 10.4028/www.scientific.net/AMR.1070-1072.1893.

[7] Qu, Hong, Jiang, He, and A. Et., "Experimental study of dynamic strain for gear tooth using fiber Bragg gratings and piezoelectric strain sensors," *Proc. Inst. Mech. Eng. Part C J. Mech. Eng. Sci.*, 2017, doi: 10.1177/0954406217744000.

[8] G. Holden, “Pellet Machine Motor Gear Box: Types, Material Standards, and Common Industrial Uses.” Accessed: Feb. 21, 2026. [Online]. Available: https://www.alibaba.com/product-insights/pellet-machine-motor-gear-box.html

[9] C. Zhang and L. Zhang, “Wind turbine pitch bearing fault detection with Bayesian augmented temporal convolutional networks,” *Struct. Health Monit.*, vol. 23, no. 2, pp. 1089–1106, Mar. 2024, doi: 10.1177/14759217231175886.

[10] V. Sharma and A. Parey, “A Review of Gear Fault Diagnosis Using Various Condition Indicators,” *Procedia Eng.*, vol. 144, pp. 253–263, Jan. 2016, doi: 10.1016/j.proeng.2016.05.131.

[11] S. R. Saufi, Z. A. B. Ahmad, M. S. Leong, and M. H. Lim, “Gearbox Fault Diagnosis Using a Deep Learning Model With Limited Data Sample,” *IEEE Trans. Ind. Inform.*, vol. 16, no. 10, pp. 6263–6271, Oct. 2020, doi: 10.1109/TII.2020.2967822.

[12] M. T. Asif, S. Ahmad, J. Ge, and M. A. Ashraf, “Multi-sensors Structural Health Monitoring of Spur Gears: A Comparative Analysis and Data Fusion Approach with Supervised Machine Learning,” *J. Fail. Anal. Prev.*, vol. 25, no. 6, pp. 2877–2892, Dec. 2025, doi: 10.1007/s11668-025-02311-7.

[13] D. M. Bourdalos and J. S. Sakellariou, “A Machine Learning Vibration-Based Methodology for Robust Detection and Severity Characterization of Gear Incipient Faults Under Variable Working Speed and Load,” *Machines*, vol. 14, no. 1, p. 9, Jan. 2026, doi: 10.3390/machines14010009.

[14] Y. Li, L. Lin, X. Ding, L. Wang, and Y. Shao, “Multi-unit Fusion Learning in the Application of Gearbox Fault Intelligent Classification Under Uncertain Speed Condition,” in *International Congress and Workshop on Industrial AI 2021*, R. Karim, A. Ahmadi, I. Soleimanmeigouni, R. Kour, and R. Rao, Eds., in Lecture Notes in Mechanical Engineering. , Cham: Springer International Publishing, 2022, pp. 330–341. doi: 10.1007/978-3-030-93639-6_28.

[15] G. Zhao, L. Liao, B. Huang, C. Liu, and C. Wei, “Wind Turbine Gearbox Fault Diagnosis Based on PNCC-STFT Voiceprint Feature Extraction and GDC- ResNet,” Dec. 01, 2025, *In Review*. doi: 10.21203/rs.3.rs-8004621/v1.

[16] M. Azamfar, “Deep Learning-based Domain Adaptation Methodology for Fault Diagnosis of Complex Manufacturing Systems,” PhD Thesis, University of Cincinnati, 2021. Accessed: Mar. 28, 2026. [Online]. Available: https://search.proquest.com/openview/de62521dbc1843b786642373c1417c75/1?pq-origsite=gscholar&cbl=18750&diss=y

[17] S.-D. Lu, H.-W. Sian, Y.-Z. Lai, and Y.-S. Lu, “A Hybrid Convolutional Extension Neural Network and K-Nearest Neighbor Approach for Multi-Sensor Wind Turbine Gearbox Fault Diagnosis,” in *2025 IEEE Industry Applications Society Annual Meeting (IAS)*, Jun. 2025, pp. 1–8. doi: 10.1109/IAS62731.2025.11061677.

[18] S. Sheng, “Gearbox Failure Modes and Mitigation | PDF | Bearing (Mechanical) | Transmission (Mechanics).” Accessed: Mar. 30, 2026. [Online]. Available: https://www.scribd.com/document/343768308/GFM-pdf