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CNN-Based Image Classification of Normal and Damaged Drill Bits for Condition Monitoring

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ABSTRACT
Drill bit failures remain one of the major causes of non-productive time and increased operational costs in drilling operations. Early detection of drill bit degradation is essential for improving drilling efficiency, reducing maintenance expenses, and preventing unexpected equipment failures. Traditional monitoring techniques rely on statistical analysis, manual inspections, and fixed-threshold approaches, which often perform poorly in complex and highly nonlinear drilling environments. This study presents a Convolutional Neural Network (CNN)-based anomaly detection framework for predictive maintenance of drill bits using an image-based dataset obtained from the Roboflow repository. The proposed framework incorporates image preprocessing, normalization, augmentation, feature extraction, and supervised deep learning classification. It used a sample size of 370 and splited the data into 70:15:15 for training, testing and validation respectively. Drill bit images were classified into normal and abnormal operating conditions. Experimental results demonstrate that data preprocessing improves model performance, increasing classification accuracy from approximately 77% to 96.59%. The developed CNN achieved precision values between 0.95 and 0.99 and F1-scores between 0.93 and 0.98 across training, validation, and testing datasets. The findings indicate that CNN-based visual inspection is an effective approach for automated drill bit condition monitoring and predictive maintenance in drilling operations.

Keywords: Anomaly Detection, Preventive Maintenance, Drill bit Monitoring, Convolutional Neural Network

INTRODUCTION

The most challenging issues related to drill bits in the oil and gas industry are mechanical wear, vibration instability, heterogeneous formations, extreme downhole conditions, and operational inefficiency, all of which significantly affect drilling performance and cost (Mitchell & Miska, 2011). Drilling equipment is most of the times subjected to harsh and challenging working conditions, which usually leads to wear and degradation of vital components. Among these vital components, drill bits represent a crucial element, as their sustained performance is significant to the success of drilling operations (Senjoba et al., 2024). When a drill bit wears out or fails, drilling must stop and the drill string is pulled out of the wellbore to be replace. This leads to significant non-productive time, increasing overall drilling cost since rig operations continue even when no drilling progress is made (Senjoba et al., 2025). Therefore, there is need to monitor any anomaly in the behaviour and performance of the drill bit. Early detection of an anomaly and preventive maintenance can mitigate and minimizes the non-productive time.

Several research have proposed different techniques to address the challenges of anomaly detection in drill bit operation. Such techniques include signal analysis, statistical techniques (Root Mean Square, Variance, Standard Deviation, Skewness and Peak-to-peak) and Machine Learning (Alharbi et al., 2023). While these techniques demonstrate effectiveness in anomaly detection, however, they come with some limitations. Signal analysis and statistical technique depend heavily on domain expertise; it requires an in-depth knowledge of statistics and data analysis. The integration of machine learning, deep learning, edge-computing, IoT, IIoT, Embedded-AI and Explainable-AI, offer a more suitable solutions to these limitations (Uddin et al., 2024).

Deep learning models such as CNN, AE, CAE, LSTM, IF, and One-Class Support Vector Machine, tend to mitigate the issue of extensive time-consuming, manual effort, and trial and error techniques in anomaly detection (Senjoba et al., 2025). That is the reason why deep learning was adopted in this study. In this study, Convolutional Neural Network (CNN) was used to analyze and detect anomaly for predictive maintenance of drill bit. It presents an early-stage anomaly detection and condition monitoring of the drill bit.

The paper provides insights into the development of fast and accurate systems for early detection of drill bit anomaly behaviour. Anomaly detection will help to reduce non-productive time of a drill bit during production. This work presents an end-to-end Convolutional Neural Network (CNN) framework for automatic detection of drill bit anomalies using image data; thereby eliminating the need for manual feature extraction and expert driven inspection. Predictive maintenance has been extensively studied for rotating machinery and manufacturing equipment, relatively few studies focus on drill bit condition monitoring through computer vision. This work extends deep learning applications to drill bit health assessment and failure prediction.

The study implements data normalization, augmentation, and image enhancement techniques that significantly improve anomaly detection performance.

The remainder of this paper is organized as follows. Section 2 presents Review of Related Works. Section 3 presents the Methodology. Performance evaluation of the proposed system is presented in Section 4. Section 5 presents the conclusion and recommendations for future work.

Review of Related Works

Predictive maintenance has become an important research area in industrial systems because of its ability to reduce equipment downtime, maintenance costs, and unexpected failures. Anomaly detection serves as a core component of predictive maintenance by identifying deviations from normal operating conditions that may indicate impending faults. A comprehensive survey by Chandola et al. classified anomaly detection techniques into statistical, distance-based, clustering-based, and learning-based approaches, highlighting the growing importance of machine learning methods for complex industrial applications Chandola et al. (2009).

Conventional machine learning algorithms such as Support Vector Machines (SVM), Decision Trees, and Random Forests have been widely applied to fault diagnosis and condition monitoring. Widodo and Yang demonstrated the effectiveness of SVMs for machine fault diagnosis, reporting improved classification performance compared with conventional statistical methods Widodo and Yang (2007). Although these approaches have achieved reasonable success, their performance typically depends on manually engineered features extracted from sensor signals or images, limiting their adaptability to different operating conditions.

Recent advances in deep learning have transformed anomaly detection by enabling automatic feature extraction from raw data. Convolutional Neural Networks (CNNs), in particular, have demonstrated remarkable success in image classification and defect detection tasks due to their ability to learn hierarchical visual representations. LeCun et al. identified CNNs as one of the key breakthroughs in modern artificial intelligence, achieving state-of-the-art performance across various computer vision applications LeCun et al. (2015). In industrial environments, deep learning models have been increasingly adopted for predictive maintenance because they eliminate the need for extensive feature engineering and improve fault detection accuracy.

Several studies have explored the application of deep learning to machinery health monitoring. Zhao et al. provided a comprehensive review of deep learning methods for machine condition monitoring and concluded that CNN-based approaches consistently outperform traditional machine learning algorithms in fault diagnosis tasks Zhao et al. (2019). Similarly, Zhang et al. developed a deep CNN architecture for bearing fault diagnosis and reported significant improvements in classification accuracy over traditional feature-based approaches Zhang et al. (2019). These findings have encouraged the adoption of deep learning models for predictive maintenance applications involving visual inspection data.

In drilling operations, condition aware monitoring is critical because drill bit wear and failure significantly affect drilling efficiency and operational costs. Conventional drill bit monitoring systems primarily rely on sensor measurements such as vibration, torque, weight-on-bit, and rate of penetration. Although these methods provide valuable operational information, they may not directly capture visual indicators of wear, fracture, or structural degradation. Therefore, computer vision-based approaches were adopted in this research and it have received increasing attention as complementary monitoring solutions.

Recent research has shown promising results using image-based artificial intelligence techniques for drill bit inspection. CNN-based models have been employed to identify wear patterns, structural defects, and cutter damage from drill bit images, enabling automated condition assessment (Senjoba et al., 2025). Furthermore, explainable artificial intelligence techniques such as Gradient-weighted Class Activation Mapping (Grad-CAM) have been integrated with CNN classifiers to improve model interpretability by highlighting regions that influence classification decisions. These approaches enhance user confidence and facilitate practical deployment in industrial environments.

Despite these advances, several challenges remain. First, many studies rely on relatively small or proprietary datasets, making it difficult to assess model generalizability (Naser, 2026). Second, most existing studies focus on classification accuracy while providing limited analysis of precision, recall, and F1-score, which are essential for evaluating anomaly detection systems in safety critical applications. Third, image-based drill bit anomaly detection remains less explored compared with vibration and sensor-based monitoring approaches (Sukeria et al., 2018). Finally, few studies investigate the impact of image preprocessing and data augmentation on model performance in drill bit predictive maintenance applications.

To address these gaps, this study proposes a CNN-based anomaly detection framework for predictive maintenance using drill bit images obtained from the Roboflow repository. Unlike traditional approaches that rely on handcrafted features, the proposed method performs automatic feature extraction through deep learning and evaluates performance using multiple classification metrics including accuracy, precision, recall, and F1-score. The study further investigates the contribution of image preprocessing and augmentation techniques toward improving anomaly detection performance.

MATERIALS AND METHODS

This section presents the methodology adopted in this research for developing an anomaly detection framework for predictive maintenance of drill bits using a Convolutional Neural Network (CNN). The methodology includes a systematic approach for data acquisition, preprocessing, feature representation, model development, training, and performance evaluation.

Block Diagram

Fig. 1 presents the overall system block diagram, stating each subsystem such as data acquisition, data preprocessing etc.

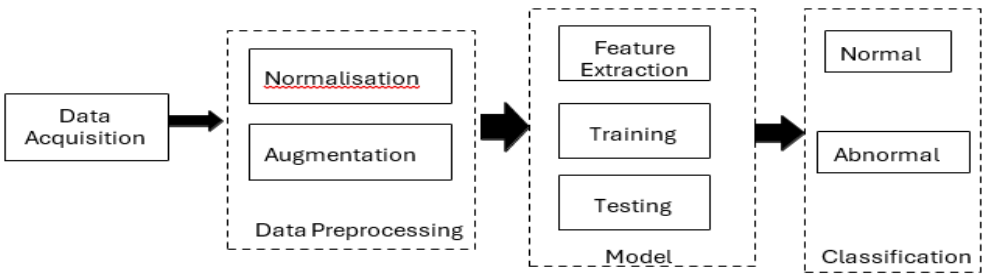


Figure 1: Block Diagram

Data Acquisition

The dataset used in this research was obtained from Roboflow computer vision dataset repository (Drill Bit, 2024). It provides annotated image datasets specifically prepared for deep learning applications, including object detection and image classification tasks. The dataset contains drill bit images representing different operating conditions. Each image contains visual information related to drill bit surface characteristics, including: cutting tooth condition, surface damage, wear patterns, missing components, structural deformation and normal operating condition. The dataset annotations are used to define the class labels required for supervised CNN training.

Dataset Preprocessing

In this study before the CNN training, the collected images of drill bit from the dataset undergo preprocessing to improve image quality and ensure consistency. The preprocessing steps taken include image resizing, pixel normalization, data augmentation and dataset splitting. The images were resized to 640 x 640 x 3 and the dataset splitting was carried out under three main categories which are Training 70%, validation 15% and Test 15%. Pixel values are normalized from the original range [0, 255] to [0, 1] using:

$$I_{norm} = \frac{I}{255} \quad (1)$$

Normalization improves numerical stability during CNN optimization. Several industrial datasets usually contain limited failure examples; image augmentation is applied to increase dataset diversity. The augmentation techniques include: Rotation, Horizontal flipping, vertical flipping, Brightness variation and Zoom transformation. Data augmentation improves CNN generalization and reduces overfitting. To prevent any potential data leakage or overfitting, the original dataset of 370 images was strictly partitioned into training (70%), validation (15%), and testing (15%). This partition was done prior to the application of any data augmentation. Image augmentation operations such as rotation, flipping and brightness adjustment were exclusively applied to the isolated training subset in order to expand its diversity, ensuring the validation and test sets remained completely unaugmented, distinct, and unbiased.

CNN-Based Drill Bit Anomaly Detection Model

A convolutional neural network is selected because of its ability to automatically learn hierarchical image features without manual feature extraction. The CNN Model was developed using MATLAB 2023a deep learning toolbox and a HP Elitebook laptop having 1Terabyte of SSD Hard disk, 16 GB of RAM and Core i7 Intel Processor of 1.80GHz frequency. The proposed CNN model consists of Input layer, Convolutional layers, Batch normalization, Activation function, Pooling layers, fully connected layers, SoftMax layer and Classification layer as illustrated in Fig. 2. The CNN performs feature extraction through convolution operations.

$$F_k = \sigma(W_k * I + b_k) . \quad (2)$$

Where:

i. F_k is extracted feature map,
ii. W_k represents convolution kernel,
iii. I represents input image,
iv. b_k represents bias,
v. σ represents activation function.

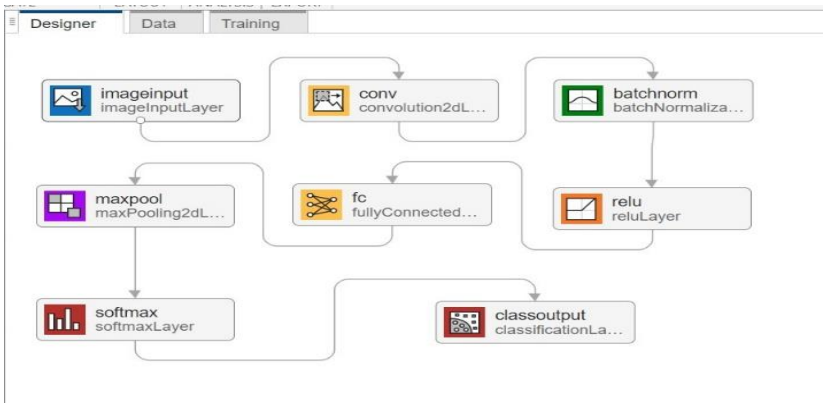


Figure 2: CNN Model Developed in MATLAB GUI

Convolution Layer

The convolution layer extracts local visual patterns such as crack boundaries, tooth deformation, surface irregularities and wear regions. The convolution operation is:

$$Y(i,j) = \sum_{n}\sum_{m} X(i+m, j+n)K(m,n) \quad (3)$$

Where:

i. K represents convolution filter,
ii. X represents input image.

Activation Function

The Rectified Linear Unit (ReLU) is adopted:

$$f(x) = max(0, x) \quad (4)$$

ReLU introduces nonlinear learning capability and improves convergence that is why it was used in this study instead of sigmoid activation function.

Pooling Layer

Max pooling is applied to reduce feature dimension for better pattern recognition:

$$P = max(x_1, x_2, \ldots, x_n) \quad (5)$$

The following advantages made it useful in this study: Reduces computational complexity, improves robustness and Prevents over fitting.

Classification Layer

The final fully connected layer predicts drill bit health condition. Softmax activation is used:

$$P_i = \frac{e^{z_i}}{\sum_{j=1}^{N} e^{z_j}} \quad (6)$$

Where:

P_i represents class probability. The class with the highest probability is selected as the predicted condition and by such method, we classified Normal drill bit from abnormal drill bit.

Model Training

The CNN model is trained using supervised learning in this study. The optimization objective is minimizing classification loss:

$L = -\sum y_i log(\hat{y_i})$ (7)

Where:

i. y_i represents true class label,
ii. $\hat{y_i}$ represents predicted probability.

The Adam optimizer is employed because of its adaptive learning capability as illustrated in Table 1.

Table 1: Training Parameters

Parameter	Value
Optimizer	Adam
Learning Rate	0.001
Batch Size	30
Epoch	50
Loss Function	Cross entropy

Table 2 present the Proposed CNN Architecture Details while Table 3 presents the image dataset profile.

Table 2: Proposed CNN Architecture Details

Layer Number	LayerType	Output Shape/Filter size	Stride/Padding	Hyperparameters/Details
1	Image Input	640 × 640 × 3		Normalisation [0, 1]
2	2D Convolution	640 × 640 × 32	Stride 1, same	Kernel size: 3 × 3
3	Batch Normalisation			Improves Training Stability
4	ReLu			Non-linear activation
5	Max Pooling		Stride 2	Pool size: 2 ×2
6	Fully Connected			SoftMax distribution
7	Classification Output			Normal Vs Abnormal

Table 3: Image Dataset Profile

Condition Class	Original Images	Augmented Images	Total Train (70%)	Total Valid (15%)	Total Test (15%)
Normal	200	415	355	30	30
Abnormal	170	353	303	25	25
Total	370	768	658	55	55

Anomaly Detection Mechanism

The anomaly detection process is formulated as an image classification problem. For an input image: X_i the CNN estimates:

$P(C \mid X_i)$ (8)

Where: C represents possible drill bit conditions.

If: $P(C_{abnormal} \mid X) > P(C_{normal} \mid X)$ (9)

The drill bit is classified as abnormal. The detected abnormal conditions provide an early warning for predictive maintenance decisions.

RESULTS AND DISCUSSION

This section presents the results obtained towards the achievement of all set objectives.

Results Obtained before Data Preprocessing

Figures 3 and 4 present the results obtained before data preprocessing. It was observed that the accuracy was not encouraging and it also indicated that there is need for proper data cleaning.



Figure 3: Results Obtained (MATLAB GUI)



Figure 4: Results Obtained (MATLAB GUI)

Results Obtained After Preprocessing

Fig. 5 presents the results obtained after a proper data preprocessing which include data cleaning, outlier removal, data augmentation and including batch processing layer into the development model.



Figure 5: Results obtained after Data Preprocessing

When the results obtained from Figs 3 and 4 was compared, there is a significant improvement. The highest accuracy obtained before data preprocessing was about 77%, but with proper data processing, the accuracy was improved to about 96%. This shows that in the dataset that was used, there are some outliers. Therefore, there is need to always clean the dataset before applying it to the model for training.

Model Performance Evaluation

The performance of the CNN model is mostly evaluated using Accuracy, Precision, Recall and F1-score. The following section presents these performance metrics as it related to our model and Table 4 describes the results obtained using the above-mentioned metrics.

Accuracy

$$Accuracy = \frac{TP+TN}{\text{TP+TN+FP+FN}} \quad (10)$$

Precision

$$Precision = \frac{TP}{\text{TP+FP}} \quad (11)$$

Recall

$$Recall = \frac{TP}{\text{TP+FN}} \quad (12)$$

F1-score

$$\text{F1} = 2\,\frac{\text{Precision x Recall}}{\text{Precision + Recall}} \quad (13)$$

Table 4: Performance Metrics

Rows	Precision	Recall	F1-Score
Test	0.99	0.98	0.98
Train	0.97	0.91	0.93
Valid	0.95	0.96	0.95

Accuracy achieved as illustrated in Figure 5 is 96.59%. It is important to note that the proposed computer vision framework presented in this work is designed as an automated surface-level diagnostic tool rather than a downhole live sensor. Drill bits operate deep within the wellbore where direct optical line-of-sight is nearly impossible, this system is meant to be integrated into standard surface inspection intervals when the drill string is pulled out of the hole.

Baseline Comparison Analysis

In order to validate the efficiency of the proposed Convolutional Neural Network (CNN) framework, its performance was benchmarked against two widely adopted standard architectures known as AlexNet and ResNet-50. All models were evaluated under identical training environments using the cleaned (preprocessed) dataset profile defined in Section III_C. Table 5 presents the summary of the baseline comparison.

Table 5: Baseline Performance Comparison

Model Architecture	Total Layers	Classification Accuracy (%)	Test F1-Score	Inference Latency (ms)
AlexNet	8	89.42	0.88	8.4
ResNet-50	50	97.15	0.98	12.8
Proposed CNN	7	96.59	0.98	4.2

As illustrated in Table V, the ResNet-50 deep architecture achieved the highest overall classification accuracy at 97.15% due to its multi-layer feature extraction and skip connections. However, this marginal 0.56% increase in accuracy over the proposed custom CNN comes at a computational penalty of the model. But in terms of F1-Score and latency, our proposed model did well. AlexNet which is structurally lighter than ResNet-50, failed to converge effectively on the high-resolution feature maps (640 ×640), yielding an accuracy of 89.42%. The proposed custom CNN model balances these trade-offs by capturing local anomalies (such as micro fractures and structural edge irregularities) while maintaining a minimal memory footprint of 14 MB and an exceptional processing latency of 4.2 ms.

CONCLUSION

This study developed a CNN-Based Image Classification of Normal and Damaged Drill Bits for condition Monitoring using image data obtained from the (Drill Bit, 2024). The proposed approach integrates image preprocessing, augmentation, deep feature extraction, and supervised classification to identify anomalous drill bit conditions. Experimental results demonstrated classification performance with an accuracy of 96.59%, precision up to 0.99, recall up to 0.98, and F1-score up to 0.98. The findings confirm the effectiveness of CNNs for automated drill bit condition monitoring. Future work should investigate explainable artificial intelligence techniques, real-time deployment on edge devices, multimodal sensor fusion, and larger industrial datasets to improve robustness and industrial applicability.

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