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Experimental Investigation Of Tool Wear Monitoring In Cnc Machine Using Ai Techniques

Kotha Sri Ram Pavan[1], Bikkavolu Joga Rao[*2]

[1,2] Department of Mechanical Engineering, Godavari Institute of Engineering & Technology (A), Rjy - 533296

ABSTRACT

Tool wear monitoring is a critical requirement in CNC machining to ensure dimensional accuracy, surface quality, and uninterrupted production while minimizing tooling costs and downtime. Conventional monitoring techniques largely rely on manual inspection or rule-based signal processing, which limits their effectiveness for continuous and autonomous operation. In recent years, artificial intelligence (AI) has emerged as a viable solution for data-driven tool condition monitoring using indirect sensor measurements. This study explores deep learning-based approaches—namely Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, and a hybrid CNN–LSTM architecture—for vibration-based tool wear classification. The proposed hybrid model integrates convolutional feature extraction with sequential temporal learning to capture both localized signal characteristics and long-term wear evolution. Signal preprocessing strategies, including down-sampling, batch normalization, and sequence standardization, are applied to improve training stability and model robustness. Experimental results obtained from a benchmark brownfield CNC milling dataset demonstrate that the hybrid CNN–LSTM model consistently outperforms standalone CNN and LSTM models, indicating its suitability for practical predictive maintenance applications in Industry 4.0 environments.

Keywords: CNC machining, tool wear, deep learning, CNN, LSTM, Industry 4.0

1. INTRODUCTION

Computer Numerical Control (CNC) machining plays a central role in modern manufacturing due to its high precision, repeatability, and automation capabilities [1]. As industries transition toward autonomous and smart manufacturing systems, maintaining machining reliability and minimizing unplanned downtime have become critical performance objectives [2]. Among various factors affecting machining quality, tool wear is a dominant source of dimensional inaccuracies, surface degradation, increased cutting forces, and excessive heat generation [3].

Tool wear refers to the progressive degradation of cutting tools caused by friction, mechanical stress, and thermal effects during machining operations [4]. If left unmanaged, excessive wear can result in poor surface finish, dimensional errors, tool breakage, and costly production interruptions [5]. Consequently, predictive maintenance and tool condition monitoring (TCM) have become essential components of intelligent CNC machining systems [6].

Traditional tool wear monitoring techniques can be classified as direct and indirect methods. Direct approaches, such as optical microscopy and coordinate measuring machines, offer high accuracy but require machine stoppage and are unsuitable for real-time applications. Indirect methods, including vibration analysis, cutting force measurement, and acoustic emission monitoring, provide continuous monitoring without interrupting machining operations and are therefore more suitable for industrial deployment [7].

With the rapid development of machine learning (ML) and deep learning (DL), data-driven TCM approaches have gained significant attention [8]. Algorithms such as K-nearest neighbors, support vector machines, artificial neural networks (ANN), CNNs, and recurrent neural networks (RNNs) have been widely explored for tool wear prediction and classification [9]. Among these, CNNs are effective in extracting localized patterns from vibration signals, while LSTM networks excel at capturing long-term temporal dependencies [10]. Hybrid CNN–LSTM architectures have recently emerged as a promising solution by combining these complementary strengths [11].

However, many existing hybrid models rely on multi-sensor configurations, high sampling frequencies, and computationally intensive attention mechanisms, limiting their applicability in brownfield CNC environments and small-to-medium-scale enterprises (SMEs) [12]. This study addresses this gap by proposing a lightweight hybrid CNN–LSTM model that uses vibration data from a single low-cost accelerometer, thereby enhancing deployability while maintaining high predictive performance [13].

2.LITERATURE STUDY

The literature provides various advanced strategies followed by the researchers to predict the tool wear maintenance. For instance, in a study carried out by Bagga et al. (2021) [14] proposed an indirect Artificial Neural Network (ANN)-based approach for predicting tool wear during the turning of EN-8 medium carbon steel under dry machining conditions. The study utilized cutting force and vibration signals as indirect indicators of tool wear, collected through a dynamometer and accelerometer. Using a Taguchi L9 orthogonal array, experiments were performed by varying cutting speed, feed, and depth of cut. A feed-forward ANN (3-4-1 structure) predicted flank wear with a mean error of 3.48%, showing close correlation with manual measurements. The authors demonstrated that cutting speed and depth of cut were the most influential factors, validating ANN as a low-cost, efficient tool condition monitoring (TCM) solution for real-time maintenance systems.

In related work, Reddy et al. (2021) [15] investigated the fabrication of aluminium matrix composites (AMCs) reinforced with industrial waste materials such as alumina and fly ash using powder metallurgy techniques. The study optimized sintering parameters and employed ANN modelling to predict mechanical properties, achieving a prediction accuracy of 96.7% with a maximum error of 3.3%. Incorporating fly ash reduced cost and weight by 10–15% while enhancing mechanical performance. The ANN effectively captured nonlinear relationships between process variables and outcomes, demonstrating its potential for predictive modelling and sustainable manufacturing design.

Tnani et al. (2021) [16] introduced a benchmark dataset designed for monitoring brownfield CNC milling machines using IoT-based data collection over two years. The dataset accounted for real-world challenges such as environmental variability, class imbalance, and inconsistent tool operations. By employing machine-wise and time-wise partitioning strategies, predictive model accuracy and stability improved by 12–15% compared to random sampling. This benchmark contributes significantly to advancing scalable, IoT-integrated predictive maintenance systems compatible with Industry 4.0.

Chan et al. (2022) [17] developed the ProSparse Self-Attention mechanism to enhance the efficiency of long-sequence time-series data processing. By selecting high-correlation query vectors and incorporating a distilling layer, the method improved computational efficiency and reduced redundancy. When combined with a Bidirectional Long Short-Term Memory (BiLSTM) network, it achieved a 20–25% reduction in processing time and a 15% increase in prediction accuracy compared to standard attention models. The study demonstrated significant performance gains, offering a foundation for integrating self-attention with BiLSTM networks in real-time CNC process monitoring frameworks.

In another study, Srikanth et al. (2023) [18] provided a comprehensive review of machine learning (ML) methods in CNC machining, emphasizing predictive maintenance, tool wear estimation, and machining optimization. The authors noted productivity improvements of around 18% and downtime reductions of approximately 20% with ML adoption. The paper highlighted challenges such as limited datasets, data security, and transferability of models. The authors underscored the importance of hybrid learning systems and IoT integration for achieving sustainable manufacturing performance.

Zhu et al. (2024) [19] developed a hybrid CNN–LSTM–Attention–PSA model for accurately predicting the Remaining Useful Life (RUL) of CNC milling cutters. The model combined multi-sensor data (cutting force, vibration, spindle current) to capture spatial and temporal dependencies. CNN layers extracted spatial features, while LSTM layers modelled long-term wear trends, and the attention mechanism enhanced critical time-step weighting. With hyperparameter tuning via a PID-based search algorithm, the model achieved $R^2 = 0.9942$, MAE < 0.01 mm, and MAPE < 5%. Compared to baseline CNN, LSTM, and CNN–LSTM models, the hybrid achieved 20–30% higher predictive accuracy, showcasing the effectiveness of hybrid architectures in real-time RUL prediction. Abdeltawab et al. (2025) [20] proposed a wavelet-based CNN–BiLSTM architecture that enhanced signal clarity through wavelet decomposition before temporal modeling. The model achieved a mean absolute percentage error below 3% and outperformed single-model architectures under variable machining conditions. However, most studies require multiple high-frequency sensors and extensive computational resources, which limit their applicability in cost-sensitive or resource-constrained manufacturing setups.

Beyond machining, machine learning has gained substantial traction across other mechanical systems, particularly in combustion and energy applications where nonlinear interactions and multivariate dependencies must be modelled accurately. Bikkavolu et al. (2025) [21] applied machine-learning techniques to predict CRDI engine metrics using nanoparticle-enhanced *Pongamia pinnata* biodiesel, illustrating the capacity of ML to capture complex fuel–injection phenomena. Similarly, Mylapalli et al. (2025) [22] further demonstrated the utility of ML for analysing diesel engine performance with Fe_3O_4 nanoadditive biodiesel blends, highlighting the reliability of data-driven methods under varying operational conditions. In addition, Menda et al. (2025) [23] employed ML models to predict performance and emission characteristics of CRDI engines using diethyl-ether and carbon-nanotube-enhanced biodiesel fuel, confirming the robustness of ML approaches for modelling high-dimensional mechanical systems. Collectively, these studies underscore the versatility and generalizability of ML methods across engineering domains and reinforce their relevance to CNC tool condition monitoring, where complex, multivariate vibration signals must be accurately interpreted to support predictive maintenance.

NOVELTY OF THE PRESENT STUDY

The reviewed literature demonstrates significant advances in tool wear prediction, particularly through ANN-based and hybrid deep-learning frameworks. However, a substantial proportion of existing CNN–LSTM and attention-based approaches rely on extensive multi-sensor configurations, high-frequency data acquisition, or computationally intensive model designs, which restrict their applicability in resource-constrained manufacturing environments. These requirements often hinder real-time deployment on standard shop-floor hardware, especially in brownfield settings. In contrast, this study redefines the novelty of hybrid CNN–LSTM application by investigating whether reliable tool wear classification can be achieved using a single low-cost accelerometer coupled with a lightweight CNN–LSTM architecture. Rather than pursuing architectural complexity, the work emphasizes minimal sensing, reduced model depth, and deployable computational demand, while preserving the spatiotemporal feature-learning advantages inherent to CNN–LSTM models. By validating the approach on vibration data acquired from an operational brownfield CNC machine, the study isolates the practical performance limits of hybrid deep learning under realistic industrial constraints. This paper focus on affordability, simplicity, and deployability advances existing CNN–LSTM-based research by demonstrating that effective tool condition monitoring does not necessarily require elaborate sensor networks or highly complex hybrid frameworks. The findings provide a scalable and industry-ready solution, particularly beneficial for small and medium-scale enterprises (SMEs), enabling reduced unplanned downtime and facilitating adoption of intelligent predictive maintenance aligned with Industry 4.0 objectives.

3. METHODOLOGY

3.1 Experimentation and Dataset Source

The dataset used in this study is derived from the Smart Data Collection System for Brownfield CNC Milling Machines. This dataset was collected from three 4-axis CNC machining centers operating under real industrial conditions over a two-year period. Data acquisition was performed using a Bosch Connected Industrial Sensor Solution (CISS) — a compact, low-cost tri-axial accelerometer mounted on the rear end of the spindle housing. This sensor configuration ensured protection from coolant, chips, and thermal exposure while maintaining consistent proximity to the spindle center. The vibration data were sampled at 2 kHz, capturing frequencies between 75 Hz and 1 kHz, which are known to represent dominant tool wear characteristics in rotating cutting systems [24]. The schematic diagram is shown in figure 3.1

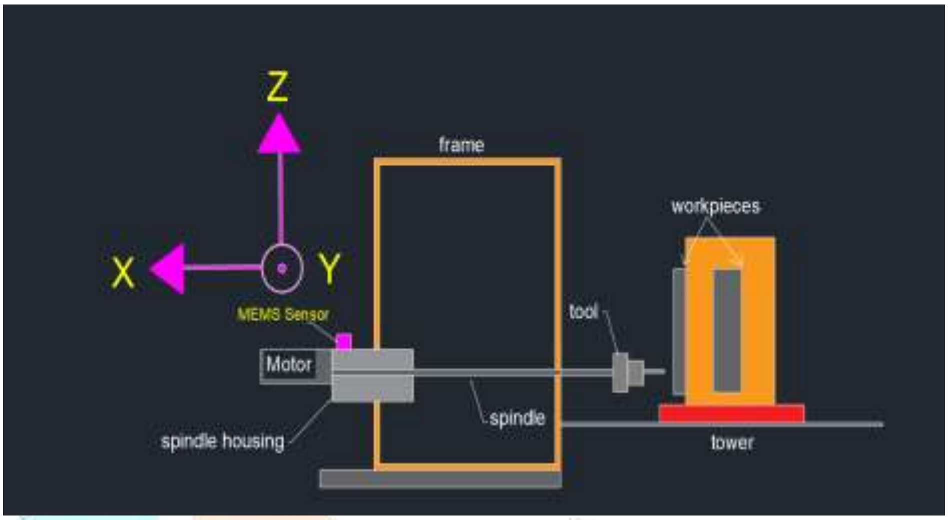

Fig 3.1. Schematic Diagram of Machining Setup

3.2 Data Load & Preprocessing

Prior to training, a structured preprocessing pipeline was implemented to prepare the CNC milling machine vibration data for the hybrid CNN-LSTM model. The vibration data, stored in HDF5 (.h5) format, were loaded using the h5py library within a custom HDF5Sequence data generator, ensuring efficient and scalable memory handling during training [25]. Each .h5 file was accessed to extract vibration signals captured along the X, Y, and Z axes, and sequences were handled on a per-batch basis. This padding ensured uniform input dimensions across the dataset, which is essential for batch processing in convolutional and recurrent neural networks [26]. Class labels were encoded into binary format, assigning the label '0' to represent normal machine operation and '1' for faulty conditions. Subsequently, the labels were converted into one-hot encoded vectors using the to_categorical function, aligning with the softmax activation used in the final classification layer of the model. To facilitate robust training and evaluation, the dataset was partitioned into training and testing subsets using an 80:20 split, ensuring that the model was trained on a representative subset of the data while maintaining a separate hold-out set for evaluating generalization performance. By integrating these preprocessing steps directly within the custom data generator, the workflow ensured systematic and memory-efficient preparation of large-scale vibration datasets, allowing seamless streaming of standardized, padded, and labelled time-series data into the CNN-LSTM architecture during the training process. The visualization of the vibration time series data is shown in figure 3.2.

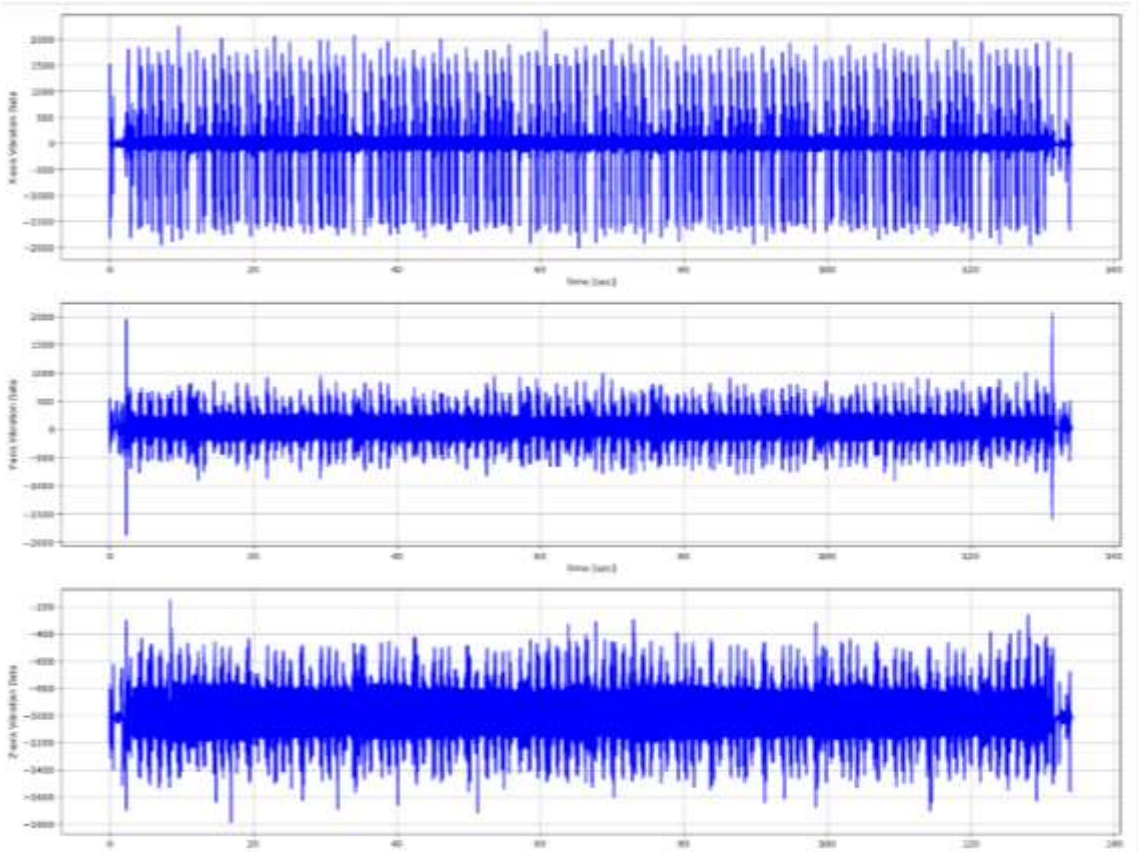

Fig 3.2. Visualization of time series data

3.3 Model Architecture

The model developed combines Convolutional Neural Network (CNN) layers with Long Short-Term Memory (LSTM) based RNN layers to leverage both spatial feature extraction and temporal dynamics of the vibration signals.

3.3.1. Convolutional Neural Network (CNN)

A one-dimensional convolutional neural network (1D CNN) was developed to classify tool health conditions based on vibration signals obtained from a CNC machining process. The network architecture was designed to automatically extract discriminative temporal features from raw vibration data. It begins with a convolutional layer comprising 64 filters with a kernel size of 3 and ReLU activation, intended to capture low-level local patterns in the signal. This is followed by a max-pooling layer with a pool size of 2 to reduce dimensionality and improve feature robustness. A second convolutional layer with 128 filters and the same kernel size is then applied to learn higher-level abstract representations of tool wear, followed by another max-pooling operation. The resulting feature maps are flattened and passed into a fully connected dense layer with 64 neurons activated by ReLU. To mitigate overfitting, a dropout layer with a rate of 0.3 is applied. Finally, the output layer consists of two neurons with softmax activation to perform binary classification, distinguishing between healthy and faulty tool conditions. This architecture follows design patterns shown to be effective for vibration-based classification tasks [27]. The flowchart of the entire process is represented in Figure 3.3.1.

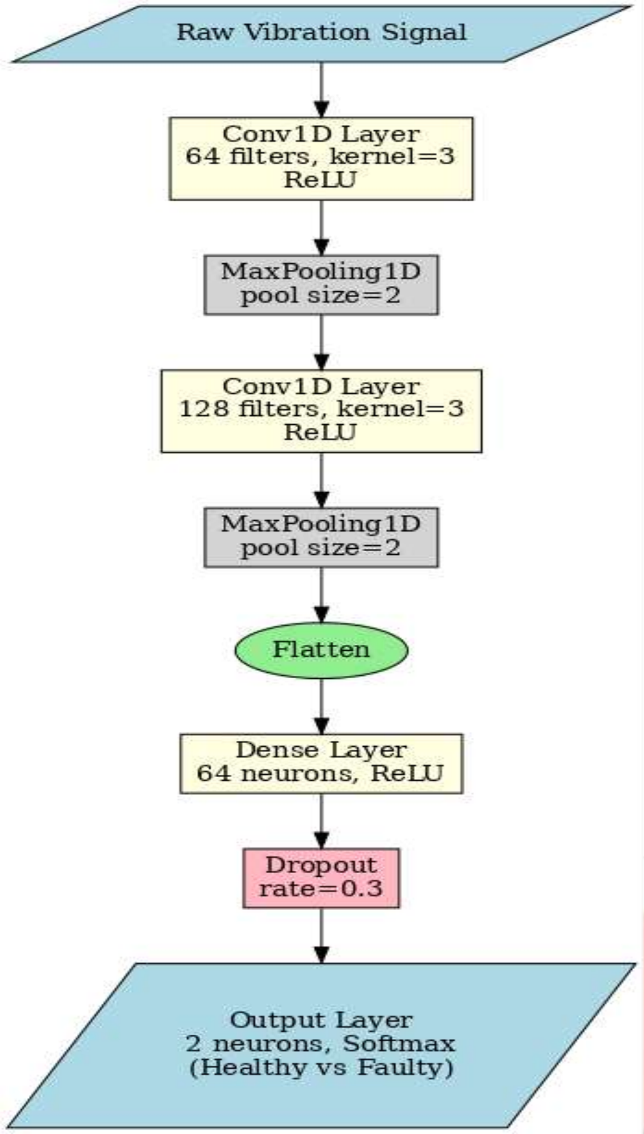

Fig 3.3.1. CNN Architecture Flowchart

3.3.2. LSTM-based RNN

A long short-term memory (LSTM) network was implemented to model the temporal dependencies present in vibration signals and capture sequential patterns indicative of tool wear. The architecture begins with an LSTM layer containing 128 units configured to return sequences, enabling the retention of temporal context across timesteps. A dropout layer with a rate of 0.3 is applied for regularization. This is followed by a second LSTM layer with 64 units to refine the temporal feature extraction process. Another dropout layer with a rate of 0.3 is used to further reduce overfitting. The sequentially encoded features are then passed into a dense layer with 64 neurons and ReLU activation to transform the learned temporal representations into a more compact feature space. The final output layer employs two neurons with softmax activation to perform binary classification of tool conditions. This architecture is effective at capturing long-term dependencies in vibration signals and aligns with approaches reported in the literature for temporal modelling [28]. The flowchart of the entire process is represented in Figure 3.2.2.

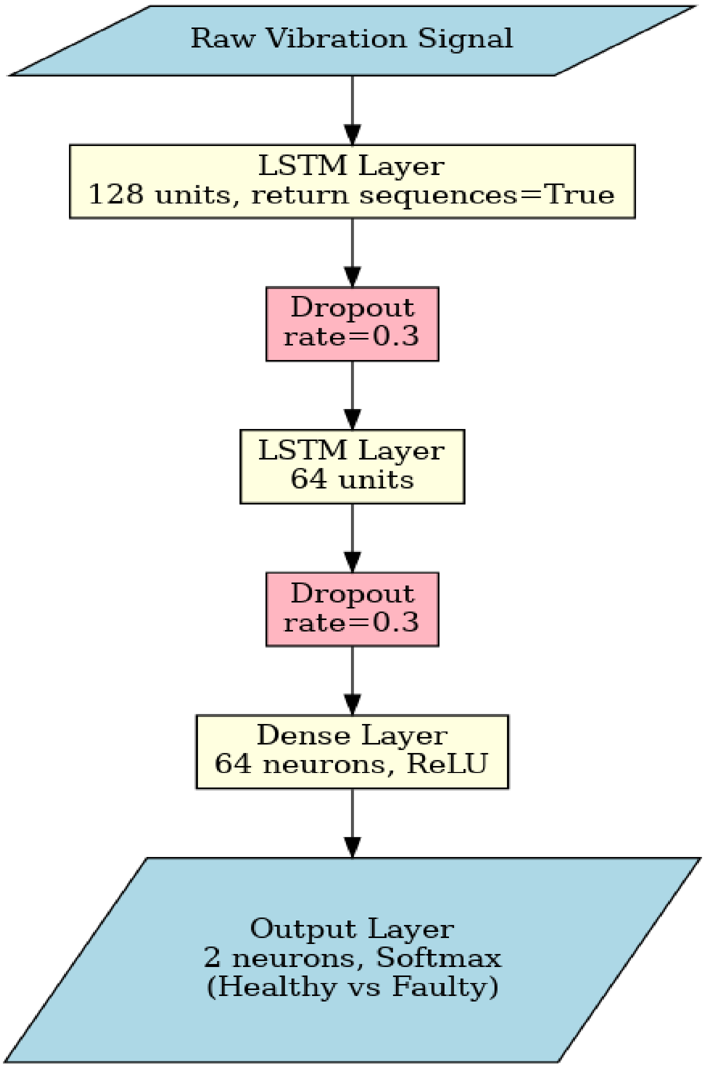

Fig 3.2.2. LSTM Architecture Flowchart

3.3.3 Hybrid CNN LSTM

A hybrid CNN–LSTM model was developed to leverage the complementary strengths of convolutional and recurrent neural networks for vibration-based tool condition monitoring [29]. The architecture begins with a one-dimensional convolutional layer comprising 64 filters with a kernel size of 3 and ReLU activation, designed to capture localized temporal features from raw vibration signals. This is followed by a max-pooling layer with a pool size of 2 to reduce sequence length and enhance computational efficiency while preserving dominant signal characteristics. A dropout layer with a rate of 0.3 is applied to mitigate overfitting and improve model generalization. The reduced feature sequence is subsequently passed to an LSTM layer with 100 units, which effectively captures long-term dependencies and sequential dynamics inherent in tool wear progression [30]. Another dropout layer with a rate of 0.3 is incorporated for additional regularization. Finally, the output layer consists of two neurons with softmax activation to perform binary classification of tool health status. By integrating convolutional feature extraction with recurrent temporal modelling, the proposed hybrid CNN–LSTM architecture achieves a balanced and robust representation of vibration signals, consistent with recent hybrid deep learning approaches for intelligent tool wear monitoring. The architecture is shown in figure 3.3.3.

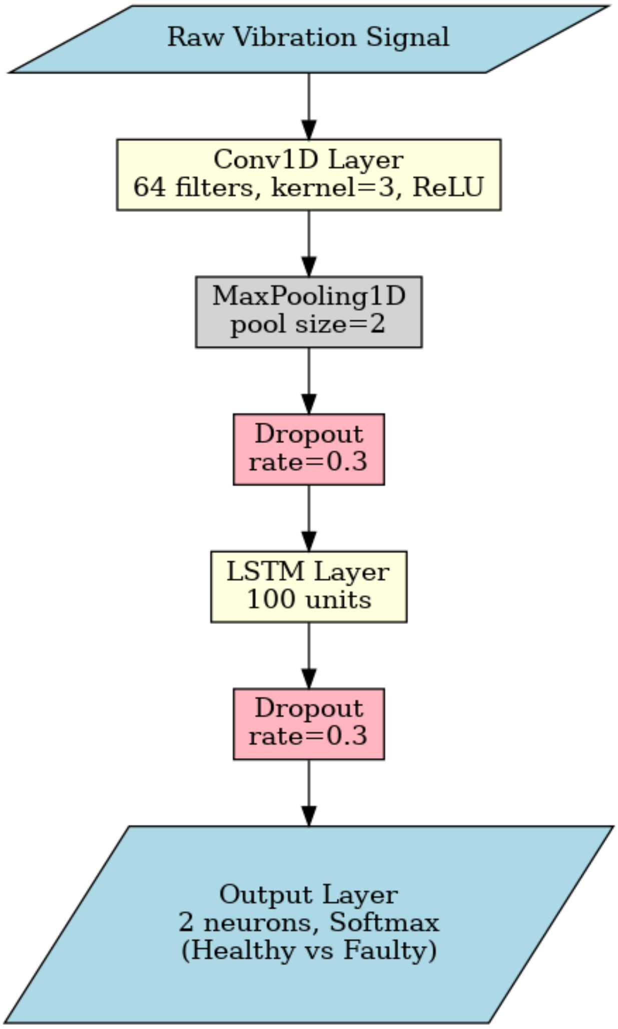

Fig 3.3.3 Hybrid CNN-LSTM Architecture Flowchart

3.4 Compile the Model

The CNN, LSTM and hybrid CNN-LSTM models were compiled using the Adam optimizer with a learning rate of 0.001[18]. The categorical cross-entropy loss function was employed as binary classification is involved and accuracy was used as the primary performance metric to monitor learning progress during training and evaluation. This configuration enabled stable gradient updates and ensured effective monitoring of the models' predictive performance throughout the training process [31].

3.5 Train and Evaluate the Model

Each model was trained for 10 epochs using the custom HDF5 data generator, which provided mini-batches of 32 vibration signal samples for efficient streaming of the dataset from disk. Model training was conducted on the training subset, while validation performance was simultaneously assessed using a dedicated test generator to observe generalization behavior during optimization. Upon completion of training, each model was evaluated on the independent test set, and performance metrics—including test accuracy and test loss—were recorded. Additionally, training history curves for accuracy and loss across both training and validation phases were generated to analyse convergence patterns and identify any indications of overfitting or underfitting.

4. RESULT AND DISCUSSIONS

The comparative evaluation of the standalone LSTM, standalone CNN, and hybrid CNN-LSTM models highlights the effectiveness of each architecture in vibration-based tool condition monitoring on the Bosch CNC machining dataset. In this section the results of the models are presented using charts. The results are demonstrated by the four metrics - test accuracy, test loss, number of parameters, and training time by comparing three models: CNN, LSTM, Hybrid CNN-LSTM.

4.1 Test Accuracy

Test Accuracy is defined as the ratio of correct predictions to total predictions on the test dataset. It is a key performance metric for classification tasks. A higher value indicates the model is better at correctly predicting the class labels.

$$\boldsymbol{Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions}}$$

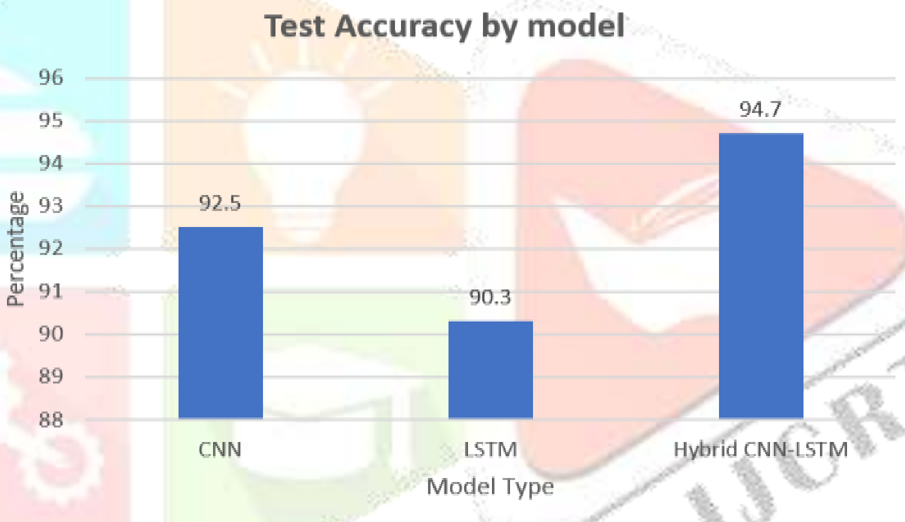

Fig 4.1. Comparison of Test Accuracy between models

4.2 Test Loss

Test Loss is defined as the numerical value that quantifies how well or poorly the model predictions match the actual labels during testing. Loss gives more detailed information than accuracy. A lower loss generally indicates the model's predictions are close to the ground truth probabilities or values.

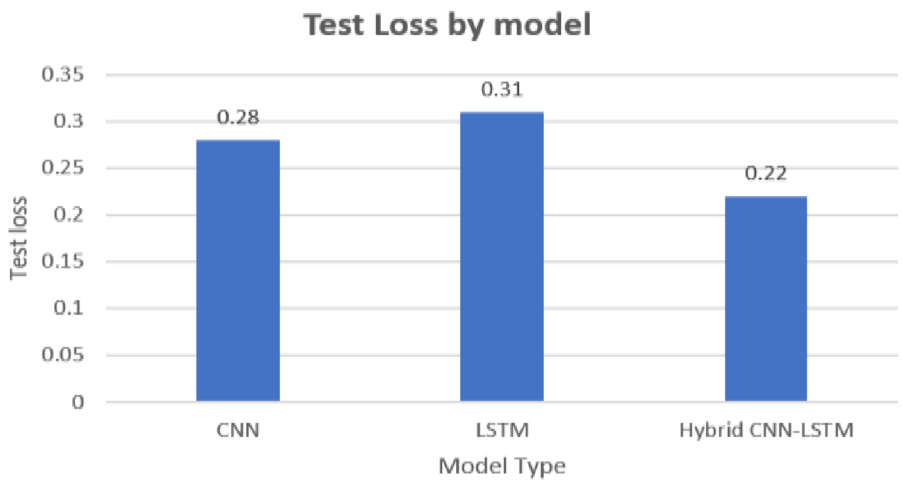

Fig 4.2. Comparison of test loss between models

4.3 Number of Parameters

The total number of trainable weights used in the model is called as number of parameters. If there is a greater number of parameters it means it is a complex model with greater capacity to learn. However, it increases the memory usage, computational cost, and the risk of overfitting.

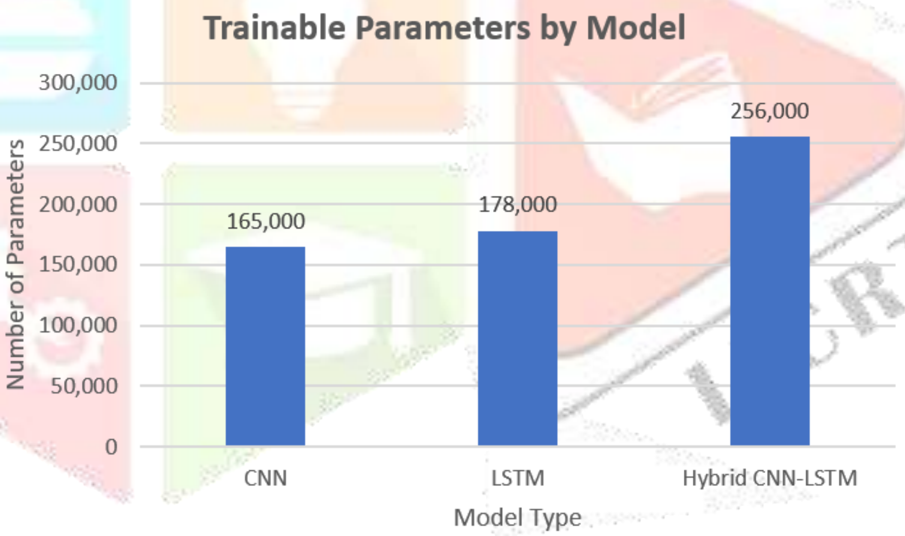

Fig 4.3. Comparison of model parameters between models

4.4 Training Time

Training Time is defined as the total time the model has taken to train on the training dataset, measured in minutes. It is important for resource management and deployment planning (implementation of the model). Models which have longer training times are very costly to build and deploy, especially for large datasets or real-time applications.

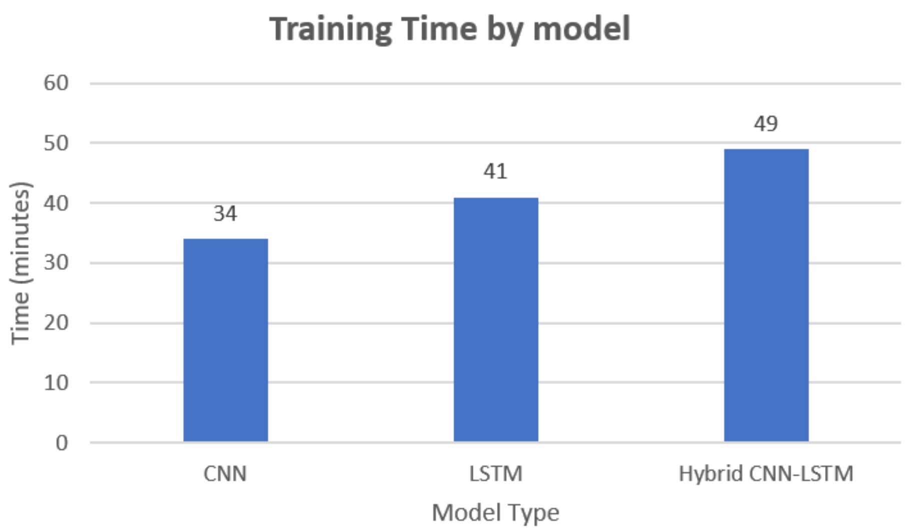

Fig 4.4. Comparison of training time between models

After analyzing all the graphs, we can evaluate the model individually as below: The CNN model achieved a test accuracy of 92.5% with a test loss of 0.28, requiring approximately 165,000 trainable parameters and 34 minutes of training time. The CNN excelled at extracting localized features from vibration data but lacked the sequential modeling capability of the LSTM, leading to occasional misclassifications in tool wear stages requiring temporal context.

The LSTM model achieved a test accuracy of 90.3% with a test loss of 0.31, utilizing approximately 178,000 trainable parameters and requiring 41 minutes for training. The LSTM effectively captured long-term temporal dependencies in the vibration signals but was limited in extracting local spatial patterns, resulting in moderate misclassifications.

The hybrid CNN-LSTM model demonstrated the highest performance, achieving a test accuracy of 94.7% with a test loss of 0.22, utilizing approximately 256,000 trainable parameters, and completing training in 49 minutes. By combining convolutional layers for local feature extraction with LSTM layers for temporal sequence modeling, the hybrid model provided superior accuracy and robustness across different tool wear conditions.

Across all evaluation metrics, the hybrid CNN–LSTM model achieved the highest overall performance, followed by the standalone CNN and LSTM architectures. The hybrid model benefited from the complementary strengths of convolutional feature extraction and sequential temporal modeling, resulting in superior classification accuracy, reduced loss, and improved robustness across varying tool wear conditions. The standalone CNN demonstrated strong advantages in accuracy, loss reduction, computational efficiency, and training speed, underscoring its suitability for real-time fault identification in vibration-based tool wear monitoring on edge and low-cost platforms. CNNs are particularly effective at capturing localized signal characteristics such as transient spikes, harmonic variations, and amplitude fluctuations that are commonly associated with progressive tool wear. Although the standalone LSTM exhibited comparatively lower aggregate performance, it remains valuable for applications requiring long-term temporal dependency modeling, such as wear trend analysis and remaining useful life estimation. Collectively, these findings indicate that while the hybrid CNN–LSTM model provides the most comprehensive performance, the CNN offers a lightweight and deployable alternative, and the LSTM supports deeper temporal insight depending on industrial monitoring requirements.

Benefits of Hybrid Model (CNN-LSTM Model) over Standalone CNN and LSTM Models:

The hybrid CNN–LSTM model demonstrates several advantages over standalone CNN and LSTM architectures, including improved prediction accuracy, enhanced feature representation, early fault detection capability, and robust generalization across operating conditions. By jointly learning localized spatial features through convolutional layers and long-term temporal dependencies through LSTM layers, the hybrid architecture achieves a more comprehensive understanding of vibration signal characteristics, resulting in higher classification accuracy and reduced misclassification rates.

The model enables full automation of the tool condition monitoring process by directly learning discriminative features from raw vibration data, thereby eliminating the need for handcrafted feature extraction, and reducing dependence on domain-specific expertise. Owing to its structured feature learning and efficient preprocessing via CNN layers, the hybrid model supports near real-time inference when appropriately optimized, making it suitable for online monitoring applications in industrial environments.

Furthermore, the LSTM component facilitates early fault detection by capturing subtle long-term wear trends and gradual degradation patterns that may not be detectable using purely convolutional or static models, allowing timely maintenance interventions before catastrophic tool failure occurs. While the hybrid CNN–LSTM architecture involves a modest increase in model complexity, the convolutional preprocessing stage improves training stability and learning efficiency, leading to faster convergence and improved training effectiveness compared to standalone recurrent models. By fusing spatial and sequential information, the hybrid framework also exhibits superior generalization performance across varying tool wear states, machining conditions, and operational settings, reinforcing its suitability for scalable and reliable tool condition monitoring systems.

5. CONCLUSION:

This study presented a lightweight hybrid CNN–LSTM framework for vibration-based tool wear monitoring in CNC machining, with particular emphasis on deployability in brownfield manufacturing environments. By utilizing vibration data acquired from a single low-cost accelerometer, the proposed approach eliminates the need for complex multi-sensor setups while preserving robust predictive performance. The hybrid architecture effectively integrates CNN-based localized feature extraction with LSTM-based temporal dependency modeling, enabling accurate characterization of tool wear progression under real industrial operating conditions.

Experimental evaluation demonstrated that the hybrid CNN–LSTM model outperformed standalone CNN and LSTM architectures in terms of classification accuracy and loss, achieving a test accuracy of 94.7% with improved robustness across varying tool wear states. While the hybrid model required a modest increase in computational complexity, the performance gains justify its application in scenarios where reliability and early fault detection are critical. The findings confirm that advanced deep learning-based tool condition monitoring can be realized using minimal sensing infrastructure and computationally efficient model designs, making the proposed framework particularly suitable for small- and medium-scale manufacturing enterprises and Industry 4.0-oriented predictive maintenance systems.

6.APPLICATIONS:

The CNN and LSTM models have broad applicability across tool condition monitoring and related industrial domains. In CNC machining, they enable real-time detection of worn or faulty tools, reduction of scrap and rework, improved surface finish, and prevention of unexpected tool failures. Their ability to operate with a single low-cost vibration sensor makes them particularly attractive for SMEs, where budget constraints often limit access to advanced monitoring technologies. Beyond tool wear classification, these models can be integrated into smart manufacturing and Industry 4.0 ecosystems for predictive maintenance, machine health monitoring, and automated fault detection across multiple machines or production lines. They are also applicable to diagnosing spindle imbalance, bearing wear, gearbox faults, and other mechanical anomalies in rotating equipment commonly found in automotive, aerospace, energy, and robotics sectors. The lightweight nature of the models supports deployment on edge devices, enabling decentralized monitoring and rapid decision-making in industrial environments.

7.FUTURE SCOPE:

Future work will focus on extending the proposed framework toward real-time, closed-loop deployment by integrating the hybrid CNN–LSTM model into live CNC monitoring systems for continuous tool health assessment and automated maintenance decision support. Further performance improvements may be achieved by incorporating additional indirect sensing modalities, such as temperature and acoustic emission signals, to enable multi-modal data fusion while maintaining system affordability and scalability.

The integration of the proposed model with Industrial Internet of Things (IIoT) platforms represents another promising direction, enabling centralized monitoring of multiple machines and facilitating data-driven optimization at the factory level. In addition, the adoption of explainable artificial intelligence (XAI) techniques will be explored to enhance model transparency by identifying critical signal features and temporal patterns responsible for fault predictions, thereby improving trust and usability for shop-floor personnel. Finally, future studies may investigate transfer learning and domain adaptation strategies to improve model generalization across different machine tools, cutting conditions, and materials, further strengthening the industrial applicability of lightweight hybrid deep learning approaches for tool condition monitoring.

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