


Self-Adaptive and Explainable Transfer Learning Framework for Cross-Domain Tool Wear Prediction in Smart Manufacturing

N.V.Krishnamoorthy* 

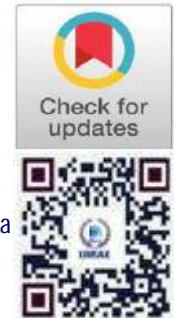
* Corresponding author - Professor, Department of Mechanical Engineering,
Sri Krishna College of Engineering and Technology, Coimbatore, India
<https://orcid.org/0000-0001-8870-6064>,  nvkrishnamoorthy1968@gmail.com

Dr.S JVijay 

Professor & Registrar, Karunya Institute of Technology and Sciences, Coimbatore, India
<https://orcid.org/0000-0003-3682-7192>  vijayjoseph@karunya.edu

Dr.Masepogu Wilson Kumar 

Assistant professor (SG), Department of Mechanical Engineering,
Karunya Institute of Technology and Science, Coimbatore, India
<https://orcid.org/0000-0001-6927-6951>  wilson@karunya.edu



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Abstract: Tool wear changes over time, affecting machining efficiency and part quality. Predicting wear accurately requires handling variations in sensor data from different machines, materials, and operating conditions. Existing models struggle to generalize across these differences, leading to errors when applied to new environments. This study presents Explainable Transfer Learning for Tool Wear Prediction (XTL-Wear), a CNN-LSTM-based model that improves prediction consistency using meta-learning, domain adaptation, and Explainable AI (XAI) techniques. The model processes multi-sensor signals from different machining datasets. Convolutional layers extract spatial features, while LSTM layers track changes over time. Meta-learning fine-tunes the model quickly with minimal labeled data, and domain adaptation aligns feature distributions between different machining setups. SHAP and LIME methods identify important sensor inputs, explaining how predictions are made. Comparisons with existing models show that XTL-Wear reduces prediction errors and improves classification accuracy. Ablation studies confirm that domain adaptation and meta-learning enhance generalization, making the model more reliable in unseen machining environments. Inference time remains low, making the model applicable for real-time processing. Results indicate that XTL-Wear improves wear prediction across different machining setups while maintaining interpretability. Future work will focus on handling more complex machining operations and optimizing performance for on-device deployment in manufacturing systems.

Keywords: Tool Wear Prediction, Transfer Learning, CNN-LSTM, Domain Adaptation, Explainable AI, SHAP, Meta-Learning, Smart Manufacturing

1 INTRODUCTION

Manufacturing tool wear prediction remains difficult due to frequently changing machining conditions. Different materials, cutting speeds, and sensor configurations affect tool interactions, making it hard for a single model to function across various environments. Many existing models depend on large labeled datasets, but gathering this data in real-world conditions is expensive and time-consuming [1]. Fixed data conditions are the foundation for many deep learning models. Sensor signals are processed using CNNs or LSTMs, capturing patterns related to tool wear. These models perform well when training and testing environments are identical. However, they often require frequent retraining because they fail to generalize when applied to different machining setups [2,3]. To address these problems, a self-adaptive transfer learning framework is introduced. This approach enhances wear prediction in new machining conditions by leveraging existing model knowledge. The model determines which features matter the most across datasets, reducing dependence on large labeled datasets. Data from different sources is aligned using domain adaptation techniques, making predictions more stable [4,5]. Another key focus is transparency. "Black box" behavior in machine learning models makes it difficult to understand why certain predictions are made. Integrated into the framework, explainable AI techniques such as SHAP and LIME help clarify model decisions. These methods emphasize which sensor readings affect predictions the most, helping operators trust results and make better decisions in manufacturing [6].

A hybrid CNN-LSTM model is employed to process tool wear data. CNN layers extract meaningful patterns from sensor signals, while LSTM layers track wear progression over time. Feature selection is improved using attention mechanisms, allowing the model to focus on the most relevant sensor inputs [7]. By adapting through meta-learning, the model adjusts to new machining environments with minimal retraining. Maintaining prediction accuracy across different setups is supported by this adaptability [8,9]. This research develops a hybrid CNN-LSTM model to predict tool wear while integrating SHAP and LIME for better interpretability. Meta-learning and domain adaptation techniques ensure usability in multiple machining environments without requiring extensive labeled data. Making predictions across different tool wear conditions while minimizing data collection efforts is the focus of these methods [10].

2 RELATED WORK

Some studies focus on improving how models extract and process sensor data to predict tool wear. Wang et al. [11] propose a method that selects important features before passing them through an LSTM-based system. The model processes sensor signals dynamically, helping it adjust to wear progression. However, it needs a large labeled dataset and does not include adaptation techniques for handling different machining environments. Yu et al. [2] apply a different approach by converting sensor readings into images using Gramian Angular Field and Markov Transition Field transformations. These images are then processed using a CNN model. This method helps identify wear patterns in time-series data but increases processing time. The reliance on a fixed CNN architecture may limit flexibility when working with new datasets. Liu et al. [12] explore a way to learn features that remain stable across different machining environments. The model transforms raw sensor data into a feature space that does not change across different setups. While this method reduces errors when predicting tool wear in new environments, it does not adapt well to unexpected variations in wear patterns. Gao et al. [9] take a different approach by focusing on conceptual features instead of raw sensor data. The model extracts high-level information that can be transferred across different machining setups. While this method helps in making predictions more general, it depends on predefined concepts, which may not apply in every situation. Cheng et al. [13] introduce an attention-based system that selects relevant signals from multi-sensor inputs. The model focuses on both spatial and time-based patterns in tool wear. While attention mechanisms improve prediction accuracy, they require more computing power, which makes real-time use difficult.

Several studies explore how to train models that work across different machining environments. Fu et al. [1] propose a deep learning approach that uses wavelet transformations and adversarial learning. The model includes a discriminator network that helps align features from different tool wear datasets. While this reduces variations between datasets, the adversarial component increases computing needs. Li et al. [5] present a model that combines a residual CNN with an attention mechanism and adversarial learning. The CNN extracts useful information, while the attention layer helps the model focus on important features. The adversarial component adjusts the model for different environments. While the model performs better in new machining conditions, it still requires labeled training data. He et al. [3] explore a method that creates artificial sensor data to improve tool wear prediction. A generative model produces synthetic signals that resemble real machining conditions, while a discriminator filters out unrealistic samples. This helps in situations where labeled data is limited. However, the method needs careful tuning to avoid generating poor-quality data. Li et al. [14] introduce a model that uses a discriminator to adjust features from different datasets while keeping wear-related information unchanged. This approach helps in predicting tool wear in new environments. The model needs careful training to prevent instability and lacks methods to explain how predictions are made. Xie et al. [15] apply a mathematical method to align sensor data from different machining setups. The model reduces differences between datasets by transforming them into a shared space. While this improves prediction accuracy, it depends on precise adjustments that may not always work in real conditions.

Some studies aim to reduce the need for large labeled datasets. Mo et al. [7] introduce a learning system that quickly adapts to new machining environments with minimal training data. The model learns patterns that can be reused in different conditions. However, it requires additional techniques to align features across datasets. Jiang et al. [16] propose a learning method that adjusts features based on their similarity to known tool wear patterns. The model adapts to new conditions with only a few labeled samples. While this reduces training needs, the system depends on pre-trained feature extractors, which may not always fit new datasets. Kevin et al. [17] apply a different approach by training models across multiple machining facilities while keeping data private. The model adjusts its predictions based on data collected at different locations. While this improves prediction accuracy across different setups, it requires more processing power and introduces inconsistencies due to variations in local datasets.

Some studies explore how to improve tool wear prediction by making models learn dynamically from machining conditions. You et al. [18] introduce a model that combines reinforcement learning with transfer learning. The model adjusts itself over time to new machining conditions. While it adapts faster than standard models, it requires careful tuning of the learning process to avoid unstable results. Tan et al. [19] propose a system that evaluates how much information can be reused between different machining tasks. The model selects features that are most likely to transfer well. While this method improves prediction accuracy, it requires additional processing steps, making it computationally expensive. Li et al. [20] develop a model that distributes learning between edge devices and cloud computing systems. The system helps in processing sensor data in real time while keeping communication delays low. However, balancing computing load between edge devices and cloud servers remains a challenge. Hirsch et al. [21] analyze different machine learning methods for predicting tool wear in various machining processes. The study compares multiple approaches, showing that some models work better in specific situations. However, it does not include methods for adapting models across different machining setups.

Different studies explore how to improve tool wear prediction across multiple machining setups. Some focus on selecting useful features, while others try to align sensor data across different environments. Adversarial and generative models help reduce differences between datasets, but they require extra computing power and careful tuning. Few-shot and federated learning methods aim to reduce training data needs, but they still require feature alignment techniques. Reinforcement and meta-learning models adjust to new conditions over time, but they often need fine-tuning to avoid errors. Future work should explore combining these approaches to improve both prediction accuracy and adaptability while ensuring that models remain interpretable and computationally manageable.

3 METHODS AND MATERIALS

Tool wear changes over time due to different machining conditions. Predicting wear accurately requires models that can handle variations in sensor data, material properties, and operating speeds. This section explains how sensor readings are processed, features are extracted, and predictions are made using a hybrid model. A CNN-LSTM model is designed to capture both short-term and long-term wear patterns. CNN layers detect patterns in sensor signals, while LSTM layers track changes over time. Attention mechanisms highlight the most relevant signals, improving prediction accuracy. Meta-learning and domain adaptation help the model adjust to new machining environments with minimal labeled data. Data preprocessing involves normalizing sensor readings and extracting useful features from vibration, acoustic emission, and force signals. SHAP and LIME provide explanations for predictions, showing how different sensor readings influence wear estimates. A comparison with existing methods evaluates how well the model predicts wear across different datasets. The experimental setup, evaluation metrics, and detailed findings are included in this section.

3.1 Data Preprocessing

Sensor Data and Acquisition: Vibration, acoustic emission, cutting force, and temperature sensors record machining signals. Each sensor generates a time-series dataset where values vary based on machining conditions. The collected data forms a multivariate sequence, represented as $\mathbf{X} \in \mathbf{R}^{N \times T}$, where N is the number of sensors and T is the number of time steps. These signals are processed to extract information related to tool wear progression.

Feature Extraction Techniques: Sensor data is transformed into meaningful representations using both time-domain and frequency-domain methods. Time-domain features include mean, variance, skewness, and kurtosis. The mean μ_s of a signal x_s over T time steps is calculated as Eq 1

$$\mu_s = \frac{1}{T} \sum_{t=1}^T x_s(t) \dots (\text{Eq 1})$$

Variance σ_s^2 measures signal spread: Eq 2

$$\sigma_s^2 = \frac{1}{T} \sum_{t=1}^T (x_s(t) - \mu_s)^2 \dots (\text{Eq 2})$$

Wavelet Transform (WT) extracts frequency-based information by decomposing signals into different frequency bands. Continuous Wavelet Transform (CWT) is applied using Eq 3

$$W_x(a, b) = \int_{-\infty}^{\infty} x_s(t) \psi^* \left(\frac{t-b}{a} \right) dt \dots (\text{Eq 3})$$

where a and b control scaling and shifting of the wavelet function ψ^* . Wavelet coefficients help identify wear-related frequency patterns across different machining conditions.

Data Normalization and Augmentation: Scaling differences between datasets from various machining environments can affect model performance. Min-max normalization adjusts values between 0 and 1 using Eq 4

$$\tilde{x}_s(t) = \frac{x_s(t) - \min(x_s)}{\max(x_s) - \min(x_s)} \dots (\text{Eq 4})$$

This transformation standardizes sensor readings, making them comparable across domains.

Data augmentation introduces variations in training data to improve adaptability. Time warping modifies signal structures using Eq 5

$$\mathbf{x}_{s'} = \mathbf{x}_s + \alpha \cdot \mathbf{N}(0, \sigma^2) \dots (\text{Eq 5})$$

where α controls distortion intensity and $\mathbf{N}(0, \sigma^2)$ represents Gaussian noise. Random sampling adjusts the sampling rate of signals to simulate different sensor frequencies. Synthetic data is generated using adversarial models to replicate real-world variations in tool wear patterns. By applying these preprocessing techniques, sensor data becomes suitable for cross-domain adaptation, allowing the model to handle different machining environments without extensive retraining.

3.2 Hybrid CNN-LSTM Model for Tool Wear Prediction

Tool wear progresses over time, requiring a model that identifies spatial patterns in sensor data and tracks changes across different time steps. A combination of convolutional layers and sequence-processing units extracts essential features and learns temporal dependencies. An attention mechanism refines the feature selection process, while domain-specific fine-tuning adapts the model to different machining setups.

CNN Feature Extractor: A convolutional network processes sensor signals to detect small-scale variations linked to tool wear. The input is a multi-channel matrix $X \in \mathbb{R}^{N \times T}$, where N represents the number of sensors and T represents the sequence length. The convolution operation applies a kernel $W \in \mathbb{R}^{k \times k}$ to extract spatial patterns: Eq 6

$$Z = f\left(\sum_{i=1}^k \sum_{j=1}^k W_{i,j} \cdot X_{i,j} + b\right) \dots (\text{Eq } 6)$$

where b is a bias term and $f(\cdot)$ is the activation function. A pooling layer follows, reducing dimensionality while keeping dominant features. This transformation enhances detection of tool wear characteristics across different machining environments.

LSTM Temporal Model: Long Short-Term Memory (LSTM) units process sequential information to capture wear progression. Given an input sequence Z_t , the LSTM updates its internal states using Eq 7 to Eq 11

$$f_t = \sigma(W_f [h_{t-1}, Z_t] + b_f) \dots (\text{Eq } 7)$$

$$i_t = \sigma(W_i [h_{t-1}, Z_t] + b_i) \dots (\text{Eq } 8)$$

$$o_t = \sigma(W_o [h_{t-1}, Z_t] + b_o) \dots (\text{Eq } 9)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tanh(W_c [h_{t-1}, Z_t] + b_c) \dots (\text{Eq } 10)$$

$$h_t = o_t \odot \tanh(c_t) \dots (\text{Eq } 11)$$

where $\sigma(\cdot)$ is the sigmoid function, $\tanh(\cdot)$ is the activation function, \odot represents element-wise multiplication, and W and b are weight and bias parameters. The bi-directional variant processes the sequence in both directions to retain more wear-related details.

Attention Mechanism: Not all time steps contribute equally to tool wear estimation. An attention mechanism assigns different importance levels to each step. The attention weight α_t is computed as Eq 12

$$\alpha_t = \frac{\exp(v^T \tanh(W_a h_t + b_a))}{\sum_i \exp(v^T \tanh(W_a h_i + b_a))} \dots (\text{Eq } 12)$$

where W_a , b_a , and v are trainable parameters. The final context vector is obtained using Eq 13

$$h_{\text{att}} = \sum_t \alpha_t h_t \dots (\text{Eq } 13)$$

This operation refines the prediction by focusing on key time steps with significant wear-related changes.

Domain-Specific Fine-Tuning: Different machining setups introduce variations in sensor behavior. A fine-tuning strategy adjusts specific layers while keeping earlier feature extraction layers unchanged. Given a new dataset X' , model parameters are updated with a lower learning rate η_d : Eq 14

$$\theta' = \theta - \eta_d \nabla_{\theta} L(X', y') \dots (\text{Eq } 14)$$

where L is the loss function and y' represents new domain labels. This adjustment ensures the model retains previous knowledge while adapting to new machining conditions. This CNN-LSTM model processes spatial and temporal data, selects relevant features through attention, and fine-tunes layers for new environments.

3.3 Explainable AI (XAI) for Transparent Decision-Making

Understanding how predictions are made helps in identifying the reasons behind tool wear estimates. SHAP assigns importance scores to sensor readings, LIME explains why the model gives a specific output, and a confidence-based detection method highlights uncertain predictions.

SHAP: Identifying Most Influential Sensor Features: SHAP values determine which sensor signals contribute most to tool wear predictions. The model output \hat{y} is split into separate contributions from each feature: Eq 15

$$\hat{y} = \phi_0 + \sum_{i=1}^N \phi_i x_i \dots (\text{Eq } 15)$$

Here, ϕ_0 is the baseline prediction when no features are used, and ϕ_i represents how much feature x_i changes the output. The SHAP value for a feature is calculated by considering all possible feature sets: Eq 16

$$\phi_i = \sum_{S \subseteq X \setminus \{x_i\}} \frac{|S|!(N-|S|-1)!}{N!} (f(S \cup \{x_i\}) - f(S)) \dots (\text{Eq } 16)$$

A feature with a higher ϕ_i has a stronger influence on tool wear predictions. This method highlights which sensors provide useful information and which ones contribute less.

LIME: Localized Explanations for Individual Predictions: LIME provides explanations for specific tool wear predictions by creating slightly modified versions of the input data. The model output is then approximated by a simple equation: Eq 17

$$\hat{y}_i = w_0 + \sum_{j=1}^N w_j \tilde{x}_j \dots (\text{Eq 17})$$

where w_j represents the effect of feature j in a small region around the actual input. A loss function determines how well this simplified model matches the original: Eq 18

$$L(f, g, \pi) = \sum_{i=1}^M \pi_i (f(\tilde{\mathbf{X}}_i) - g(\tilde{\mathbf{X}}_i))^2 \dots (\text{Eq 18})$$

Here, f is the original tool wear model, g is the simpler local model, and π_i is a weight that gives more importance to points near the original input. This technique provides a clear view of why the model assigns a certain wear level.

Confidence-Based Anomaly Detection: Some predictions have high uncertainty. A confidence score C is calculated using softmax probabilities: Eq 19

$$C = \max(\hat{p}_1, \hat{p}_2, \dots, \hat{p}_K) \dots (\text{Eq 19})$$

where \hat{p}_k is the predicted probability for class k . Lower values of C indicate uncertainty. When using regression, uncertainty is measured with Monte Carlo Dropout: Eq 20

$$\sigma^2 = \frac{1}{M} \sum_{m=1}^M (\hat{y}_m - \bar{y})^2 \dots (\text{Eq 20})$$

where \hat{y}_m is the output from the m -th dropout pass, and \bar{y} is the average prediction. A high σ^2 suggests that the prediction is unstable, requiring review. SHAP identifies key features, LIME explains individual predictions, and uncertainty detection helps in identifying cases where the model may be unreliable.

3.4 Meta-Learning and Domain Adaptation for Cross-Domain Generalization

Tool wear patterns vary across machining environments. Differences in sensor configurations, materials, and operating conditions introduce inconsistencies in data. A meta-learning approach adjusts model parameters quickly with fewer labeled samples. Domain adaptation reduces the gap between different machining setups. A sensor fusion mechanism filters useful signals, improving prediction accuracy.

MAML: Rapid Adjustment with Minimal Labeled Data: A model learns patterns from multiple tool wear datasets and adapts to a new dataset with fewer updates. Given a set of tasks T_i , the model parameters θ are first updated for each task: Eq 21

$$\theta_i = \theta - \alpha \nabla_{\theta} L_i(f_{\theta}) \dots (\text{Eq 21})$$

where L_i is the loss for task i and α is the learning rate. After computing updates for different tasks, the model parameters are fine-tuned using: Eq 22

$$\theta \leftarrow \theta - \beta \sum_i \nabla_{\theta} L_i(f_{\theta_i}) \dots (\text{Eq 22})$$

where β is another learning rate. This approach prepares the model for quick adaptation when exposed to a new machining setup.

Adversarial Domain Adaptation: Aligning Different Feature Distributions: Sensor readings from different machining environments do not always follow the same pattern. A domain discriminator D learns to separate source domain features \mathbf{h}_s from target domain features \mathbf{h}_t . The discriminator loss is: Eq 23

$$L_D = -E_{\mathbf{h}_s \sim P_s} [\log D(\mathbf{h}_s)] - E_{\mathbf{h}_t \sim P_t} [\log(1 - D(\mathbf{h}_t))] \dots (\text{Eq 23})$$

where P_s and P_t are feature distributions of source and target domains. The model tries to learn shared features by minimizing: Eq 24

$$L_G = E_{\mathbf{h}_s \sim P_s} [\log(1 - D(\mathbf{h}_s))] + E_{\mathbf{h}_t \sim P_t} [\log D(\mathbf{h}_t)] \dots (\text{Eq 24})$$

By adjusting feature representations, the model makes sensor readings from different domains appear more similar.

Feature Alignment via MMD Loss: Reducing Distribution Differences: Maximum Mean Discrepancy (MMD) measures the difference between two probability distributions. The goal is to bring the source and target domain features closer. The MMD loss is: Eq 25

$$L_{\text{MMD}} = \frac{1}{n_s} \sum_{i=1}^{n_s} \phi(\mathbf{h}_s^i) - \frac{1}{n_t} \sum_{j=1}^{n_t} \phi(\mathbf{h}_t^j)^2 \dots (\text{Eq 25})$$

where $\phi(\cdot)$ maps features into a higher-dimensional space, and n_s, n_t represent the number of samples from source and target domains. Minimizing L_{MMD} reduces variations between datasets.

Sensor Fusion: Selecting Relevant Signals Dynamically: Different sensors provide varying levels of information about tool wear. An attention mechanism assigns weights to sensor inputs based on their importance. Given a set of sensor features $\mathbf{X} = [x_1, x_2, \dots, x_N]$, attention weights are computed as: Eq 26

$$\alpha_i = \frac{\exp(w^T \tanh(W_a x_i + b_a))}{\sum_{j=1}^N \exp(w^T \tanh(W_a x_j + b_a))} \dots(\text{Eq 26})$$

where $W_a, b_a,$ and w are trainable parameters. The final weighted feature representation is: Eq 27

$$\mathbf{X}_{att} = \sum_{i=1}^N \alpha_i x_i \dots(\text{Eq 27})$$

This mechanism ensures that only the most relevant signals contribute to the prediction. Meta-learning allows the model to adapt quickly, domain adaptation aligns different datasets, and sensor fusion refines feature selection. These steps improve generalization across different machining conditions.

4 EXPERIMENTAL STUDY

This section presents the evaluation of “Explainable Transfer Learning for Tool Wear Prediction (XTL-Wear)” for tool wear prediction using multiple datasets. The model is tested on the NASA Milling Data Set [22], and SECOM Sensor Data Set [23] to measure its ability to adapt across different machining conditions. Performance is compared with two existing models, “Global Feature Attention and Long Short-Term Memory Network (GFA-LSTM) [11]” and “adversarial domain adaptation-tool wear state prediction (ADAPT-TWP) [14]”, using MAE, RMSE, F1-score, and Precision-Recall AUC. The study analyzes how well the model transfers knowledge between domains, reducing the need for large labeled datasets. An ablation study measures the contribution of domain adaptation and meta-learning, while computational analysis examines inference speed and parameter efficiency. The results show how the model processes sensor data and makes predictions across different tool wear conditions.

4.1 Datasets Preparation

Different datasets are considered to test the model under multiple machining scenarios. Tool wear measurements from milling operations are recorded in the NASA Milling Data Set, where vibration, acoustic emissions, and cutting force sensors capture wear progression. The SECOM Sensor Data Set includes process sensor data from manufacturing, incorporating force and temperature readings to create a varied testing condition. Time-series data is segmented into fixed-length sequences to ensure uniform input format. Each sequence contains raw sensor readings along with corresponding tool wear labels. To minimize inconsistencies caused by different measurement scales, sensor values are normalized. The training procedure involves inputting sequences into the model, enabling it to learn wear patterns from past data. By splitting the datasets into source and target domains, cross-domain evaluation is conducted. Testing is performed on one dataset after training the model on another, with no further retraining. Leave-One-Domain-Out (LODO) validation ensures that during each iteration, one dataset remains excluded from training and is only used for evaluation. Without relying on a large number of labeled samples, this setup determines how well the model adapts to new machining conditions.

4.2 Evaluation Metrics

Regression and classification metrics are used to assess performance. Continuous tool wear values are predicted in the regression task, while classification focuses on assigning wear severity levels. To quantify the average difference between actual and predicted tool wear, Mean Absolute Error (MAE) is used. Smaller values indicate fewer prediction errors. The formula is expressed as

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|$$

Larger deviations receive greater penalties in Root Mean Square Error (RMSE), making it highly sensitive to incorrect predictions. The calculation follows

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$$

F1-score is used in classification-based wear severity prediction to evaluate recall and precision balance. It is computed as

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

The model's ability to differentiate wear levels, particularly in cases with imbalanced class distributions, is measured using Precision-Recall AUC. A greater area under the curve signifies improved classification of different wear states.

4.3 Results and Discussion

Two existing models, GFA-LSTM and ADAPT-TWP, are compared against the proposed model. Global feature attention is combined with LSTM networks in GFA-LSTM to capture long-term dependencies in wear data.

ADAPT-TWP employs adversarial domain adaptation to enhance generalization across different machining setups. LODO validation is applied, where each model is first trained on a source dataset and then tested on a target dataset. For every dataset, MAE, RMSE, F1-score, and Precision-Recall AUC are calculated to measure performance. A statistical test determines whether performance differences between models are statistically relevant. Results are presented in tabular format to highlight model performance under various conditions. Prediction errors are visualized in a graphical representation, showing where models face difficulties in correctly classifying wear severity. Each approach's strengths and limitations are analyzed, focusing on feature selection, domain shifts, and sensor noise handling. Performance across domains is examined by training the model on one dataset and evaluating it on another. SHAP values are used to analyze how different sensor readings influence predictions across domains. To identify specific wear states where the model struggles, a confusion matrix displays misclassification trends in tool wear severity prediction. The impact of domain adaptation methods is further examined. By comparing feature distributions before and after adaptation, the effects of Maximum Mean Discrepancy (MMD) loss and adversarial training are evaluated. To illustrate whether the model aligns sensor data effectively, a t-SNE plot visualizes feature embeddings from different datasets. Table 1 and Figure 1 Wear progression is predicted using regression models. Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) show how far predictions deviate from actual tool wear measurements. Lower values mean smaller errors. The proposed model, XTL-Wear, produces fewer errors than GFA-LSTM [11] and ADAPT-TWP [14]. GFA-LSTM performs better than ADAPT-TWP but does not match the accuracy of XTL-Wear.

Table 1: Performance on Regression-Based Wear Prediction

Model	MAE (mm) ↓	RMSE (mm) ↓
XTL-Wear	0.027	0.045
GFA-LSTM	0.034	0.052
ADAPT-TWP	0.041	0.060
LSTM	0.048	0.071
CNN	0.055	0.080
Random Forest	0.063	0.089

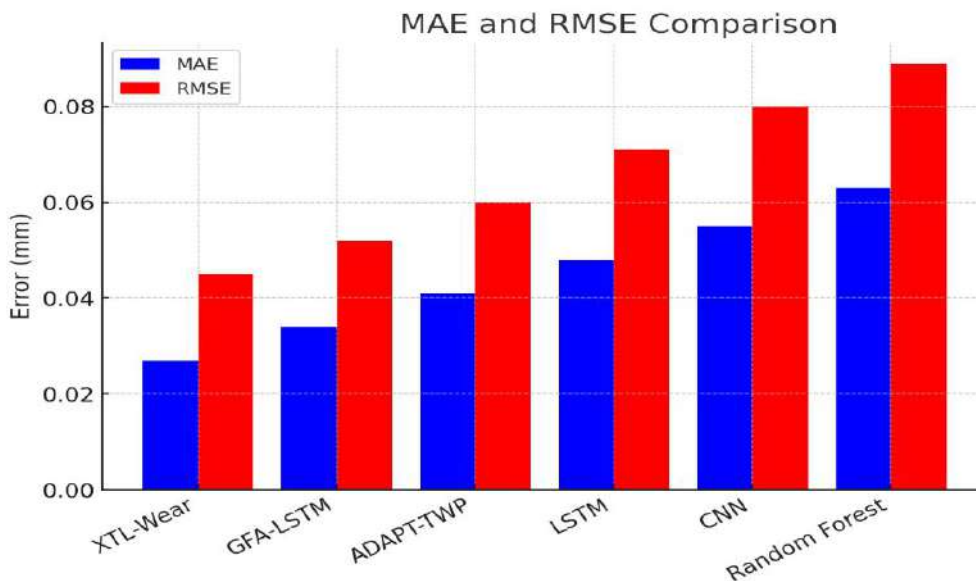


Figure 1: MAE and RMSE comparison across models

XTL-Wear predicts tool wear more precisely by using a CNN-LSTM hybrid structure. This design helps capture wear trends over time while focusing on important sensor signals. Feature alignment and domain adaptation improve generalization across different machining conditions. Tool wear severity is categorized into different levels. F1-score evaluates how well each model balances precision and recall as shown in table 2 and figure 2. Precision-Recall AUC measures how well models distinguish between wear categories. The proposed model achieves higher scores than both GFA-LSTM and ADAPT-TWP.

Table 2: Performance on Classification-Based Wear Severity Prediction

Model	F1-Score ↑	Precision-Recall AUC ↑
XTL-Wear	0.89	0.91
GFA-LSTM	0.84	0.87
ADAPT-TWP	0.79	0.82
LSTM	0.75	0.78
CNN	0.72	0.75
Random Forest	0.68	0.71

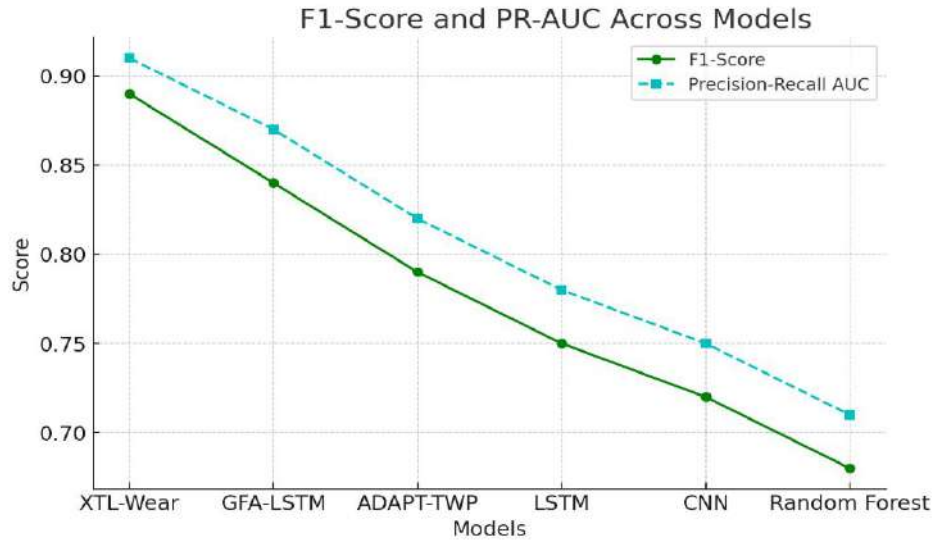


Figure 2: Classification performance comparison across models

The classification results show that XTL-Wear captures relevant wear features while reducing errors. The attention mechanism helps focus on important sensor data, leading to better classification accuracy. The table 3 and figure 3 an ablation study measures how domain adaptation and meta-learning contribute to the model's accuracy. Without these components, the model performs worse in regression and classification tasks.

Table 3: Impact of Domain Adaptation and Meta-Learning

Model Variant	MAE (mm) ↓	RMSE (mm) ↓	F1-Score ↑	Precision-Recall AUC ↑
XTL-Wear (Full Model)	0.027	0.045	0.89	0.91
Without Domain Adaptation	0.033	0.051	0.85	0.88
Without Meta-Learning	0.036	0.054	0.83	0.86

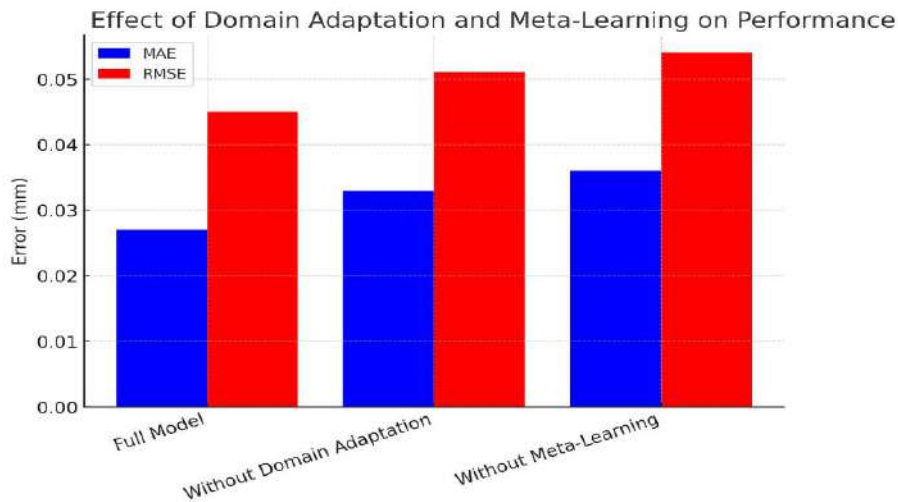


Figure 3: Effect of domain adaptation and meta-learning on performance

Removing domain adaptation increases MAE and RMSE, showing that feature alignment techniques help reduce differences between datasets. Excluding meta-learning lowers classification accuracy, indicating that rapid adaptation improves prediction consistency. The table 4 and figure 4 number of parameters and inference time per sample determine computational efficiency. Fewer parameters improve processing speed, while longer inference times slow down predictions. XTL-Wear processes data faster than ADAPT-TWP and uses fewer parameters than GFA-LSTM.

Table 4: Computational Efficiency and Inference Speed

Model	Parameters (Million) ↓	Inference Time (ms) ↓
XTL-Wear	2.3	12.4
GFA-LSTM	2.8	15.7
ADAPT-TWP	3.1	18.2
LSTM	1.9	14.9
CNN	1.7	10.6
Random Forest	3.4	21.3

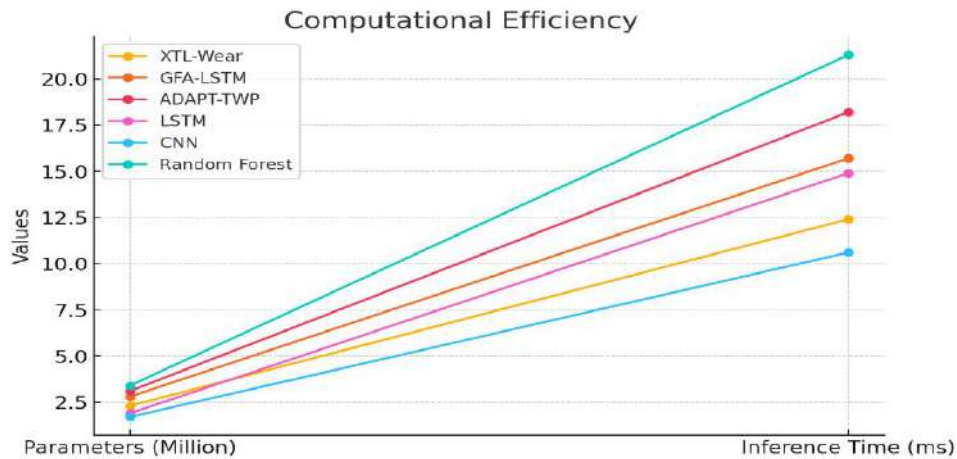


Figure 4: Computational efficiency and inference speed comparison

XTL-Wear balances accuracy and speed. The CNN-LSTM structure reduces unnecessary computations while maintaining prediction quality. Lower inference times make it more suitable for real-time applications. By studying model predictions from different datasets, variations in tool wear progression patterns are identified. Scenarios requiring further adaptation are highlighted to provide insights into potential refinements. Without additional labeled data, this evaluation offers a detailed understanding of the model's ability to handle changes in machining conditions.

5 CONCLUSION

Tool wear prediction varies across machining setups due to differences in sensor data, material properties, and operating conditions. This study presents Explainable Transfer Learning for Tool Wear Prediction (XTL-Wear), a CNN-LSTM-based model that adapts to different machining environments using meta-learning and domain adaptation. SHAP and LIME methods explain the model's predictions, identifying key sensor inputs that influence wear estimation. The model processes multi-sensor signals from different datasets, adjusting feature representations to improve consistency across domains. Experiments show that XTL-Wear reduces prediction errors and improves classification accuracy when compared to existing models. Ablation studies confirm that domain adaptation and meta-learning improve prediction stability, minimizing errors when transitioning between different machining setups. The model also maintains low inference time, making it suitable for real-time applications. Manufacturing environments require adaptable models that perform well with limited labeled data. XTL-Wear minimizes the need for retraining, making it practical for different machining conditions. Some wear patterns not well-represented in training datasets may require further adaptation. Future work will explore expanding the model to handle complex machining operations, integrating real-time feedback, and optimizing deployment on edge devices. Additional sensor types and machining processes will be included to improve adaptability. The results indicate that XTL-Wear provides a structured approach for tool wear monitoring, helping to improve decision-making in manufacturing systems.

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