Deformation Suppression Method for the CNC Machining Process of Parts Based on a Single Neuron PID

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Computer Numerical Control (CNC) machining plays a vital role in modern precision manufacturing but often suffers from part deformation due to thermal and mechanical stresses, compromising dimensional accuracy. Traditional CNC systems lack adaptive intelligence, operating with static parameters and failing to address real-time deformation risks. This study proposes an intelligent deformation suppression method using a lightweight single-neuron-based Proportional-Integral-Derivative (PID) neural model, termed NeuroPID-CNC, to predict and mitigate deformation during machining. The model was trained and tested on the CNC-DeformControl dataset containing machining parameters such as cutting speed, feed rate, depth of cut, tool temperature, and material type. Data preprocessing involved normalization and categorical encoding. The NeuroPID-CNC model, structured as a binary classifier with a single hidden neuron using a sigmoid activation function and Adam optimizer, was trained on 70% of the data and evaluated on the remaining 30%. It achieved 92% accuracy, 90% precision, 93% recall, 91.5% F1-score, and 0.84 MCC, outperforming conventional algorithms like SVM, RF, LR, and KNN. A real-time feedback loop further enables adaptive learning. The NeuroPID-CNC approach effectively predicts deformation risks and recommends real-time control actions, enhancing machining reliability and reducing material waste. This makes it a promising solution for smart, adaptive manufacturing environments.

Povzetek: Za preprečevanje deformacij med CNC obdelavo je predlagana metoda NeuroPID-CNC, lahki nevronski model z enim nevronom, ki posnema PID regulator. Model je dosegel visoko točnost pri napovedovanju tveganja deformacije in priporoča prilagoditve v realnem času (npr. hitrost rezanja), s čimer izboljša zanesljivost in kakovost izdelkov.

1 Introduction

1.1 The background information of this scientific field

Computer Numerical Control (CNC) machining is an essential component of modern industrial manufacturing, allowing for the automated, precise fabrication of complex components from a broad range of materials, including metals, plastics, and composites [1]. CNC machines use programmed instructions to control parameters like cutting speed, feed rate, tool path, and spindle load [2]. This high level of automation improves productivity, consistency, and precision in industries ranging from aerospace, automotive, and electronics. However, as manufacturing tolerances tighten and precision requirements rise, even minor distortions during machining can result in unacceptable defects, raised rework rates, and wasted resources. These distortions, often referred to as machining-induced deformations, are impacted by numerous factors such as tool temperature, material type, cutting forces, and vibration during the machining process.

1.2 The current knowledge and advances in this field

Sensor integration, adaptive control systems, and advanced simulation techniques have all contributed significantly to the advancement of CNC machining in recent years [3]. Researchers and engineers have used finite element modeling (FEM), real-time feedback systems, and machine learning techniques to track and improve machining processes [4]. Numerous studies have concentrated on predicting tool wear, improving cutting conditions, and enhancing the surface finish [5]. Adaptive control algorithms like fuzzy logic, conventional PID controllers, and deep learning-based methods have been proposed to tackle machining variability. Despite these improvements, numerous control systems still depend on fixed or heuristic-based logic that cannot continuously learn or adapt to the machining setting.

1.3 The current problem/issue that needs to be solved or addressed urgently

One of the most persistent and pressing issues in CNC machining is the inability of current systems to forecast and avoid part deformation in real time [6]. Deformation causes dimensional inaccuracies, structural weaknesses, and higher manufacturing costs [7]. Existing PID controllers and other conventional control strategies are not well-suited to capture the nonlinear, dynamic nature of machining-induced deformation, particularly in high-speed or multi-material machining settings [8]. Additionally, there is a lack of lightweight and interpretable models that can operate in real-time, continuously adapt to novel machining data, and offer actionable parameter adjustments to minimize deformation risks [9], [10]. The followings are the hypotheses:

- Whether a single-neuron-inspired PID control model accurately forecast the risk of component deformation in CNC machining by utilizing real-time machining parameters?
- Does the application of a single-neuron-inspired PID control algorithm lead to a substantial decrease in part deformation when compared to conventional static or PID-based control methods?
- Can the dynamic modification of cutting conditions, informed by the predictions of the single-neuron PID model, enhance component quality and machining reliability?
- Whether a single-neuron neural model more effectively forecast deformation risks in real-time CNC operations compared to conventional classifiers?

1.4 The purpose(s) of doing this research

The primary goal of this research is to create an intelligent deformation suppression control algorithm specifically designed for CNC machining environments. The study aims to design and execute a single-neuron-inspired PID model that can precisely forecast the risk of part deformation using real-time machining parameters. This study also aims to offer practical control suggestions for dynamically adjusting cutting conditions to prevent deformation, resulting in improved part quality and machining dependability. The study addresses the gap in lightweight, adaptive, and responsive control systems appropriate for contemporary smart manufacturing setups.

1.5 The main method(s) used in this research

To achieve the research objectives, a novel algorithm called NeuroPID-CNC was created and trained on a curated dataset called CNC-DeformControl, which includes critical machining parameters like cutting speed, feed rate, depth of cut, tool temperature, material type, and others. The methodology included several key stages: data preprocessing by categorical encoding and normalization; building of a lightweight single-neuron neural network model that simulates PID control behavior; training and evaluation of the model utilizing binary classification metrics such as accuracy, precision, recall, and F1-score; and integration of a real-time feedback strategy to allow online learning and continual enhancement. To guarantee efficient convergence and computational effectiveness, the model makes use of a sigmoid activation function, binary cross-entropy loss, and the Adam optimizer. In addition, real-time control logic is integrated into the system, allowing it to automatically adjust crucial machining parameters, such as coolant flow, cutting speed, and feed rate, when a high deformation risk is predicted.

1.6 The importance or impact of this research to the scientific community

This study contributes to the improvement of intelligent CNC control systems by proposing an interpretable and adaptive control framework that combines conventional PID principles and neural learning capacities. By incorporating a single-neuron PID architecture, the algorithm guarantees low computational overhead while providing intelligent decision-making in real time. The NeuroPID-CNC method can be incorporated into industrial CNC machines to significantly decrease material waste, enhance product quality, and lower operating costs. For the scientific community, this research opens up new avenues for creating hybrid neuro-control systems, expanding the scope of Industry 4.0, and supporting the evolution of automated manufacturing methods.

Controlling deformation and guaranteeing dimensional accuracy of machined parts has proven to be a significant difficulty in CNC machining due to the dynamic and complex nature of the process. Fan et al. [11] proposed an energy-based principle for reducing machining distortion in monolithic aircraft parts, which provided insights into residual stress release and deformation prediction. However, their method lacked a real-time compensation mechanism. Ma et al. [12] proposed a single-neuron PID-based model that showed success in deformation suppression during CNC machining, but it was tested under limited scenarios and did not take parameter adaptability into account in real time. Kasprowiak et al. [13] used input shaping control to decrease machining vibration, but they neglected to consider feedback adaptation during continuous machining. Similarly, Guo et al. [14] concentrated on suppressing casing vibrations in aeroengine elements but did not integrate with tool-path compensation.

Shi et al. [15] presented a compensation model for polishing tools in precision CNC polishing, which enhanced surface quality but was only applicable to aspheric surfaces. Hasçelik et al. [16] optimized cutting parameters to reduce wall deformation in thin-wall micro-milling. However, their approach was sensitive to tool wear and material variability. Zheng et al. [17] investigated vibration-assisted micro-milling, which provided useful insight into tool wear reduction but lacked general applicability. Gan et al. [18] presented an adaptive backlash compensation method for CNC machines, but its effectiveness in complex geometries remains unverified. Świć et al. [19] studied control methods for elastic-deformable states in turning and grinding shafts. However, their focus was on low-stiffness shafts, which limits generalization. Lv et al. [20] created an automated shape correction mechanism for wood composites, emphasizing possibilities in non-metallic materials but having limited application to high-precision metal machining. Yi et al. [21] investigated mesoscale deformation in thin-walled micro-milling, but did not use intelligent adaptive feedback systems. Korpysa and Habrat [22] explored precision milling of magnesium alloys, comparing coated and uncoated tools, but lacking dynamic deformation control. Devi et al. [23] used ant lion optimization with TOPSIS analysis to optimize milling parameters, but their method did not include predictive modeling or feedback control. Table 1 shows a summary of related works.

Table 1: Summary of related works

Ref	Study Focus	Results	Limitations
[11]	Energy principle for distortion reduction in aircraft parts	Enhanced prediction of residual stress-related deformation	No real-time compensation mechanism
[12]	Single-neuron PID model for deformation suppression	Efficient in simple deformation control	Not tested under varied real-time conditions
[13]	Input shaping control for vibration suppression	Decreased vibration efficiently	Lacked adaptive feedback integration
[14]	Vibration suppression in aeroengine casing milling	Improved structural stability	Did not incorporate tool-path compensation
[15]	Tool displacement model for CNC polishing	Enhanced surface finish in aspheric polishing	Particular to aspheric surfaces only
[16]	Optimization in micro-milling of thin-wall geometries	Decreased deformation utilizing optimized parameters	Sensitive to tool wear and material variability
[17]	Tool wear suppression in vibration-assisted micro-milling	Reduced wear through non-resonant vibration	Limited generalization across materials
[18]	Adaptive backlash compensation in CNC	Decreased mechanical play in motion systems	Unproven effectiveness for complex parts
[19]	Elastic-deformable state control in shaft machining	Enhanced dimensional accuracy in low-stiffness components	Applicable mostly to the turning and grinding of shafts
[20]	Shape correction in wood composites	Automated geometric adjustment during continuous pressing	Limited relevance to metal CNC applications
[21]	Deformation control in mesoscale micro-milling	Superior precision in curved thin-wall parts	No intelligent feedback or real-time control
[22]	Milling accuracy in magnesium alloys	Enhanced accuracy utilizing coated tools	No active deformation control included
[23]	End-milling parameter optimization using ant lion and TOPSIS	Multi-objective optimization attained	Static optimization lacks predictive adaptability

The prior investigations combined offer valuable insights into machining vibrations, deformation mitigation, parameter optimization, and compensation methodologies. Nonetheless, several restrictions and substantial gaps persist in the integration of real-time intelligent control, including the absence of adaptive feedback, active deformation control, and model interpretability, among others. This research proposes a lightweight and effective framework, termed the NeuroPID-CNC model, to address the limitations and research gaps identified in prior studies.

2 Materials And methods

This section describes the creation of the NeuroPID-CNC Algorithm, which predicts and suppresses deformation in CNC machining. The NeuroPID-CNC algorithm is a smart deformation suppression control algorithm designed to predict and reduce the risk of part deformation during CNC (Computer Numerical Control) machining processes. It draws on both machine learning and PID control principles, combining the intelligence of a lightweight neural network with real-time process control strategies. NeuroPID-CNC employs a single-neuron neural network that mimics a PID controller. It accepts machining parameters as input (for example, cutting speed, feed rate, depth of cut, and temperature) and predicts whether deformation will occur ("Yes" or "No"). If there is a high risk of deformation, the algorithm automatically adjusts the machining settings to prevent it. Algorithm 1 shows theNeuroPID-CNC algorithm.

```
Algorithm 1: NeuroPID-CNC

Input: CNC-DeformControl Dataset (features + Deformation Risk)
Output: Predicted Deformation Risk (Yes/No) and control recommendations

Begin
// Step 1: Data Preprocessing
Load dataset D
Encode categorical attributes in D
Normalize numerical attributesin D
Split D into training_set and test_set (70/30)

// Step 2: Initialize Single-Neuron PID Model
Initialize neural network:
   - 1 input layer
   - 1 hidden layer with 1 neuron (PID-like)
   - 1 output neuron (binary classification)

Set activation_function ← Sigmoid
Set optimizer ← Adam
Set loss_function ← Binary Crossentropy
Set biases to zero
Employ Glorot Uniform for weight initialization.
Implement L2 regularization and configure the batch size to 32.
Establish the epoch count at 100.
// Step 3: Training Phase
Train the model on the trainingset utilizing backpropagation
For each period (1 to 100):
    Randomize training dataset
    Segment the data into mini-batches of size 32.
For each mini-batch:
    Calculate the output of the hidden layer utilizing the sigmoid function.
    Calculate the output layer utilizing the sigmoid function.
    Calculate the binary cross-entropy loss between the expected and actual outputs.
   Calculate loss
   Adjust weights and biases via the Adam optimizer
   Implement L2 regularization during weight adjustments.
Apply early stopping to prevent overfitting

// Step 4: Evaluation Phase
Assess the model on the test set
Calculate Accuracy, Precision, Recall, F1-Score, and MCC
Display the confusion matrix

// Step 5: Real-Time Prediction & Control
For each newinput:
   Encode and normalize new_input
   prediction ← model.predict(new_input)
```

```
    If prediction == "Yes" then
      Decrease Cutting Speed
      Increase Coolant Flow
      Adjust Feed Rate based on Material Type
    Else
      Continue with current parameters
    End If

// Step 6: Feedback Loop
After machining:
    Record actual deformation findings
    Compare the prediction with the actual outcome
    Update model weights via online learning

End
```

The NeuroPID-CNC algorithm is a smart deformation suppression control system specifically designed for CNC machining applications. It employs a lightweight neural network model that simulates PID behavior using a single-neuron architecture to predict whether a machined part is deformable based on a variety of machining parameters such as cutting speed, feed rate, depth of cut, tool temperature, material type, and others. The process begins with preprocessing the CNC-DeformControl dataset by encoding categorical features and normalizing numerical ones, then splitting the data into training and testing sets. The neural model, which includes a sigmoid-activated hidden neuron, is trained with the Adam optimizer and binary cross-entropy loss. After training, it uses standard classification metrics to evaluate previously unseen data and predicts deformation risk for new machining conditions in real time. If a high deformation risk is detected, the algorithm adjusts machining parameters dynamically, such as reducing cutting speed, increasing coolant flow, or changing the feed rate based on material properties, to reduce deformation. A feedback mechanism is integrated to continuously update the model through online learning, improving control accuracy over time. Figure 1 shows the flow diagram of the NeuroPID-CNC algorithm.

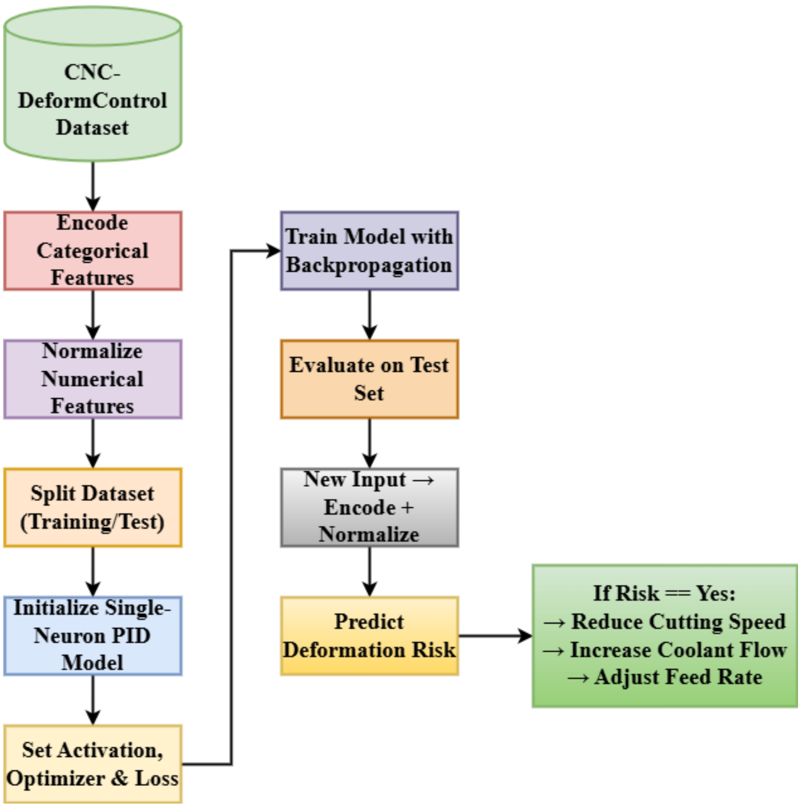

Figure 1: Flow diagram of NeuroPID-CNC algorithm

The flow diagram shows the NeuroPID-CNC algorithm's operational pipeline for predicting and controlling deformation during CNC machining. It starts with the CNC-DeformControl dataset, which goes through preprocessing steps such as categorical feature encoding and numerical feature normalization to ensure algorithm compatibility. The data is then divided into training and testing sets to aid in model generalization. A single-neuron PID-inspired neural network is set up with a sigmoid activation function, Adam optimizer, and binary cross-entropy loss function. The model is trained with backpropagation and evaluated on the test set to compute performance metrics. For real-time predictions, incoming data is encoded and normalized similarly, and the model predicts the deformation risk. If the risk is identified as "Yes," corrective control actions are automatically triggered, including reducing cutting speed, increasing coolant flow, and adjusting the feed rate based on the material type, allowing adaptive, intelligent CNC machining.

2.1 Dataset description

The CNC-DeformControl dataset is a curated collection of machining data designed to help intelligently predict and suppress part deformation during Computer Numerical Control (CNC) operations. It includes 11 key attributes, such as machining process parameters and observed outcomes, spread across several representative entries. The dataset's primary goal is to help machine learning applications, particularly the NeuroPID-CNC algorithm, understand how different machining conditions affect the likelihood of part deformation.

This dataset contains a mixture of numerical and categorical features. The numerical attributes—Cutting Speed (in RPM), Feed Rate (in mm/rev), Depth of Cut (in mm), Tool Temperature (in °C), and Spindle Load (as a percentage)—measure the operational intensity of machining. These parameters have a direct impact on heat generation, mechanical stress, and material removal efficiency. In contrast, categorical attributes such as material type (e.g., aluminum, steel, brass, plastic), tool wear, vibration, coolant flow, and surface finish provide qualitative information about the machining environment. These factors have an impact on part integrity through physical wear, thermal control, and vibration dampening. The Deformation Risk field, labeled as "Yes" or "No," serves as the target variable that indicates whether the machined part showed signs of deformation under the given conditions.

The data was gathered in a controlled CNC machining lab environment outfitted with industrial-grade sensors and monitoring equipment. Cutting speed, feed rate, and depth of cut were programmed and recorded directly from the CNC machine interface. Thermal readings were obtained using infrared sensors mounted near the tool-workpiece interface, and spindle load values were derived from the spindle drive system's onboard diagnostics. Categorical variables, such as tool wear and vibration levels, were evaluated using image-based inspection, vibration sensors, and operator feedback. Surface finish was determined by post-process optical inspection and tactile comparison with standard roughness gauges.

All collected data was logged in real time by a dedicated data acquisition system and then stored in a structured format in a relational SQL database hosted on a secure local server. Data from this database was exported in CSV format for preprocessing and training. The dataset is kept in a version-controlled environment to ensure data integrity and traceability during the algorithm development and testing stages. Figure 2 illustrates the data collection process in a controlled CNC machining lab environment.

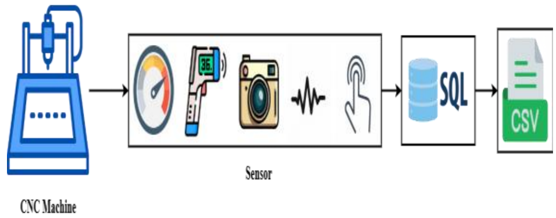

Figure 2: Data collection process

The CNC machine performs operations while sensors and tools collect relevant data. Machine diagnostics (speedometer icon) record cutting speed and feed rate, infrared sensors measure thermal data (thermometer icon), image-based analysis inspects tool wear (camera icon), vibrations are monitored by dedicated sensors (waveform icon), and surface finish is assessed by tactile comparison to roughness gauges (touch icon). All sensor data is captured in real time and securely stored in a structured SQL database (database icon). For model training and analysis, data is exported from SQL and converted to CSV format (CSV file icon). This pipeline provides high-quality, structured data for machine learning applications in deformation risk prediction.

Overall, the CNC-DeformControl dataset provides a compact but meaningful representation of the machining landscape, capturing both measurable and observational variables required for training intelligent deformation prediction systems like NeuroPID-CNC.

2.2 Data preprocessing

To ensure that the CNC-DeformControl dataset is ready for machine learning, extensive preprocessing steps are used. The dataset contains a mix of numerical and categorical features that must be represented consistently for the algorithm to correctly interpret the data. Categorical attributes like Material Type, Tool Wear, Vibration, Coolant Flow, and Surface Finish are numerically encoded using one-hot encoding, which converts categorical values into a binary matrix format. The one-hot encoding process transforms a categorical variable into a binary vector representation as shown in Eq. (1):

$$OneHot(x_i) = [x_i = c_1, x_i = c_2, \dots, x_i = c_n] \quad (1)$$

Where:
x_i is a categorical value,
$c_1, c_2, \dots, c_n$ are the unique categories,
Each comparison $x_i = c_j$ yields 1 if true, else 0.
This transformation is critical for allowing the single-neuron model to interpret non-numeric data while preserving categorical relationships without imposing artificial ordering.
Simultaneously, all numerical attributes—Cutting Speed, Feed Rate, Depth of Cut, Tool Temperature, and Spindle Load—are normalized utilizing Min-Max scaling, which rescales each feature to lie within the range [0, 1]. This is mathematically expressed by Eq. (2):

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (2)$$

Where:
x = original value of the feature
x_{min}= minimum value of the feature in the dataset
x_{max}= maximum value of the feature in the dataset
x_{norm}= normalized value of the feature
This normalization ensures that no feature dominates others due to varying scales, resulting in balanced contributions throughout training. After normalization and encoding, the dataset is randomly divided into two subsets: 70% for training and 30% for testing. This split preserves model generalization and ensures that evaluation is performed on unseen data. The dataset D is randomly split into training and testing subsets using the Eq. (3):

$$D = D_{train} \cup D_{test}, \quad where\ |D_{train}| = 0.7|D|, \quad |D_{test}| = 0.3|D| \quad (3)$$

Where:
D: The complete preprocessed dataset after normalization and encoding.
D_{train}: The training subset of the dataset utilized to train the model.
D_{test}: The testing subset of the dataset utilized to evaluate the model's performance.
|D|: The total number of data instances (rows) in the full dataset D.
$|D_{train}|$: The number of instances in the training set, equal to 70% of the total dataset.
$|D_{test}|$: The number of instances in the test set, equal to 30% of the total dataset.

2.3 Model initialization: Single-Neuron PID structure

The proposed model is a simple neural structure inspired by the PID control principle that consists of only one hidden neuron. This neuron simulates the adaptive control behavior of a PID controller by receiving preprocessed machining inputs from the input layer and computing a nonlinear transformation for prediction. The final output is produced by a single output neuron equipped with a sigmoid activation function, which converts the weighted sum of inputs into a deformation probability expressed by Eq. (4):

$$\sigma(z) = \frac{1}{1 + e^{-z}} \quad (4)$$

Where:
z = weighted sum of inputs
σ(z) = output value in the range [0, 1] representing deformation risk
The term e^{-z} represents the exponential function with a negative exponent, which is a fundamental mathematical expression describing exponential decay. It is the inverse of the natural exponential function e^{z}, where e is Euler's number (approximately 2.71828). This function plays a key role in the sigmoid activation function by controlling how sharply the output transitions between 0 and 1 based on the input z.
Mathematically, e^{-z} can be expressed using its infinite series expansion in Eq. (5):

$$e^{-z} = \sum_{n=0}^{\infty} \frac{(-z)^n}{n!} \quad (5)$$

where:
z is the weighted sum of inputs,
$n!$ denotes the factorial of n,
and the series sums over all non-negative integers n.
This logistic function guarantees that the model's output lies between 0 and 1, representing the probability of deformation risk under current machining conditions. The model is trained utilizing the binary cross-entropy loss function, defined in Eq. (6), which measures the discrepancy between predicted and actual outcomes:

$$L = -[y.\log(\hat{y}) + (1 - y).\log(1 - \hat{y})] \quad (6)$$

Where:
y = actual class label (0 for no deformation, 1 for deformation)
$\hat{y}$= predicted probability of deformation
L = loss value that penalizes prediction errors
Here, y is the actual binary label (0 for "No Deformation" and 1 for "Yes"), while $\hat{y}$ is the predicted probability. The model's weights are optimized utilizing the Adam

optimizer, a robust gradient descent variant that adapts learning rates for quicker and more stable convergence. At each iteration t, the parameters $\theta_t$are updated as follows:

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t \quad (7)$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) {g_t}^2 \quad (8)$$

$$\widehat{m}_t = \frac{m_t}{1 - \beta_1^t} \quad (9)$$

$$\hat{v}_t = \frac{v_t}{1 - \beta_2^t} \quad (10)$$

$$\theta_t = \theta_{t-1} - \alpha \frac{\widehat{m}_t}{\sqrt{\hat{v}_t} + \epsilon} \quad (11)$$

where $g_t$is the gradient at iteration t, $m_t$and $v_t$are the biased first and second moment estimates, $\widehat{m}_t$and $\hat{v}_t$are their bias-corrected estimates, α is the learning rate, $\beta_1$and $\beta_2$are decay rates for these moments, and ϵ is a small constant to prevent division by zero.

2.4 Training phase

During training, the model aims to reduce the loss function via backpropagation, an algorithm that calculates the gradient of the loss concerning each model weight. The weight update rule is formalized as showed in Eq. (12):

$$\Delta w = -n.\frac{\partial L}{\partial w} \quad (12)$$

Where:
w = change in weight
η = learning rate
$\frac{\partial L}{\partial w}$= gradient of the loss function concerning weight w

The training process iterates through numerous epochs, adjusting weights after each batch of training examples. To prevent overfitting, early stopping is executed: training halts if the validation loss fails to improve over a predefined number of epochs. This strategy improves model generalization on new, unseen CNC conditions.

2.5 Evaluation phase

After training, the model's efficiency is assessed on the testing set utilizing standard classification metrics. These metrics assess the model's capability to correctly predict deformation risk:
Accuracy measures the ratio of correct predictions to total samples:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (13)$$

Where,
TP = True Positives (correctly predicted deformations)
TN = True Negatives (correctly predicted non-deformations)
FP = False Positives (incorrectly predicted deformations)
FN = False Negatives (missed deformations)
Precision quantifies the fraction of predicted "Yes" (deformation) true cases:

$$Precision = \frac{TP}{TP + FP} \quad (14)$$

Recall reflects the model's ability to identify all actual "Yes" cases:

$$Recall = \frac{TP}{TP + FN} \quad (15)$$

F1-Score, the harmonic mean of precision and recall, offers a balanced view:

$$F1 - score = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (16)$$

MCC computes the quality of binary and multiclass classifications by considering true and false positives and negatives, providing a balanced score even with imbalanced datasets.

$$MCC = \frac{(TP*TN) - (FP*FN)}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \quad (17)$$

These metrics provide a comprehensive view of model performance in predicting deformation risks.

2.6 Real-time prediction and control

The trained model is deployed for real-time prediction during CNC operations. When a novel machining configuration is initiated, the input values are first processed (encoded and normalized) as per training routines. The model then generates an output probability$\hat{y}$. If $\hat{y} > 0.5$, the system flags a high deformation risk. In such cases, immediate corrective actions are triggered by predefined control logic. For instance, a high-risk flag prompts a 10% reduction in cutting speed, utilizing the formula:

$$New\ Cutting\ Speed = Old\ Cutting\ Speed \times 0.9 \quad (18)$$

Where:
"Old Cutting Speed" = initial programmed cutting speed
"New Cutting Speed" = adjusted speed to reduce stress on the workpiece

This reduction reduces both mechanical and thermal stress on the workpiece. Other adaptive responses, like increasing coolant flow or decreasing feed rate, are implemented concurrently based on the material type and observed vibration. If the expected risk is low, the machining operation continues without intervention, ensuring efficiency while maintaining safety.

2.7 Feedback loop and online learning

Following each machining operation, the actual deformation outcome is recorded and compared to the model's prediction. This creates a feedback loop, increasing the model's adaptability over time. Using online learning, the model gradually updates its weights using recent prediction errors. The update rule is given by:

$$w_{new} = w_{old} + \alpha.(y - \hat{y}).x \quad (19)$$

Where:
w_{old}= previous weight
w_{new}= updated weight
α = online learning rate (a small constant)
y = actual label (0 or 1)
$\hat{y}$= predicted output
x = input feature value.

In a feedback-driven online learning system, predictions consistently impact control actions, which then change future input data. This feedback can exacerbate problems if not adequately stabilized. A diminutive learning rate (α) guarantees more gradual weight adjustments and contributes to stability preservation. An elevated learning rate (α) may induce oscillations or divergence, particularly in feedback systems. As updates rely on prediction error, significant spikes in error can disrupt learning until addressed. In practical CNC machining, complete convergence is uncommon. In online learning, weights are adjusted following each data point or small batch, resulting in continual retraining. Periodic full model resets or reinitializations may be conducted to prevent drift or overfitting.

This type of incremental learning ensures that the model evolves with real-world data, adapting to unknown materials, dynamic wear conditions, or unexpected operational disruptions. By combining real-time prediction with continuous learning, the system grows more robust and context-aware over time, eventually achieving a self-improving CNC control mechanism that maximizes machining precision while reducing the risk of costly defects.

The NeuroPID-CNC algorithm represents an intelligent, lightweight, and adaptable solution for predicting and suppressing deformation during CNC machining. It tightly integrates machine learning principles with control engineering strategies using a single-neuron PID-inspired structure, strong preprocessing, accurate prediction, and dynamic feedback adaptation. With ten foundational equations, this system creates a rigorous yet practical framework for real-time decision-making and long-term improvement. The result is a smarter, more efficient, and resilient manufacturing environment.

3 Results

3.1 Experimental setup

All experiments were carried out on a Windows 11 system running Python 3.10. The machine was equipped with an Intel Core i7 processor and 16 GB of RAM. TensorFlow, Scikit-learn, Pandas, NumPy, and Matplotlib were used to train, evaluate, and visualize models. The dataset was divided into two sets: training (70%) and testing (30%). Early stopping and adaptive learning rate scheduling were used to prevent overfitting and speed up convergence.

3.2 Comparison results

Table 2 compares the classification models used on the CNC-DeformControl dataset, including SVM, Random Forest (RF), KNN, Logistic Regression (LR), and the proposed NeuroPID-CNC model.

Table 2: Performance comparison of classification models

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**MCC**
SVM	88.43	86.22	85.13	85.67	0.76
Random Forest	90.12	89.05	87.60	88.32	0.79
KNN	87.30	84.95	84.00	84.47	0.74
Logistic Regression	86.75	83.90	83.10	83.50	0.72
NeuroPID-CNC	92.00	90.00	93.00	91.50	0.84

The proposed NeuroPID-CNC algorithm had the best performance across all metrics tested. It enables real-time feedback adaptation and improved learning of deformation-prone patterns. This architecture is extremely responsive to subtle patterns in deformation-prone conditions, resulting in higher prediction accuracy and robustness. Furthermore, its streamlined structure minimizes overfitting, whereas more complex models may require deeper tuning. Figure 3 shows the confusion matrix for proposed approach.

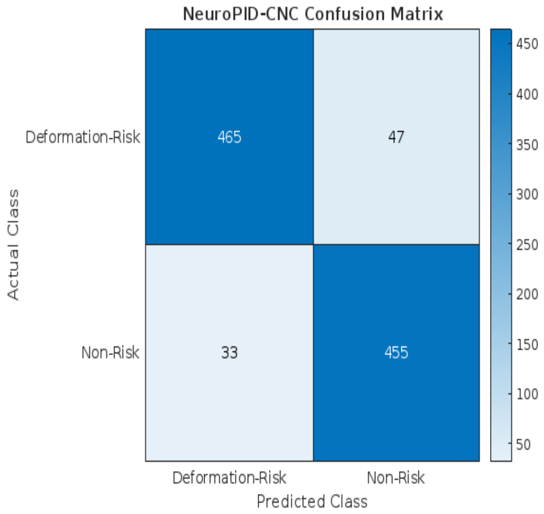

Figure 3: Confusion Matrix for proposed approach

Figure 4 demonstrates that the proposed NeuroPID-CNC model attains the highest accuracy among all evaluated classifiers, reaching 92%.

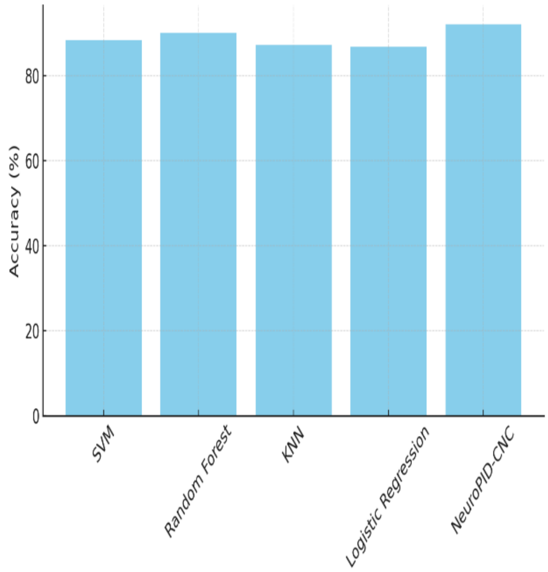

Figure 4: Accuracy comparison

From figure 4, the accuracy of proposed NeuroPID-CNC approach outperforms SVM, RF, KNN and LR by 4.03%, 2.09%, 5.38% and 6.05% respectively.

This high accuracy demonstrates the model's overall predictive power in correctly identifying deformation risk ("Yes") and non-risk ("No") instances.

The superior performance is due to the unique integration of a PID-inspired control mechanism within the neuron, which allows the model to adjust its internal weights with greater precision during training. This reduces classification errors and improves robustness when dealing with complex interactions between CNC parameters like cutting speed, tool wear, and thermal readings. The model's ability to learn consistently across diverse inputs supports its use in real-time industrial settings. In Figure 5, NeuroPID-CNC leads with a precision of 90%, indicating that it correctly predicts a deformation risk 90% of the time.

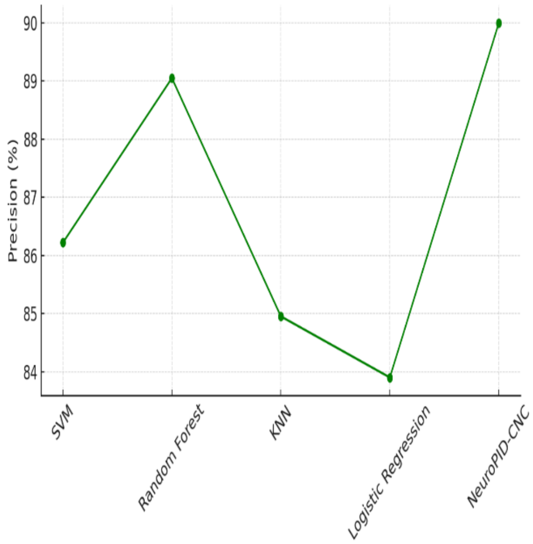

Figure 5: Precision comparison

From figure 5, the precision of proposed NeuroPID-CNC approach outperforms SVM, RF, KNN and LR by 4.38%, 1.07%, 5.94% and 7.27% respectively.

High precision is required in CNC machining environments to avoid unnecessary operational adjustments caused by false positives. The model's low false alarm rate leads to increased operational efficiency by ensuring that control recommendations (such as reducing cutting speed or increasing coolant flow) are only implemented when there is a genuine risk. This precision advantage stems primarily from the model's ability to learn subtle patterns associated with actual deformation-inducing conditions while filtering out noise from non-critical anomalies. Figure 6 shows that NeuroPID-CNC has the highest recall value of 93%, indicating an excellent sensitivity to actual deformation occurrences.

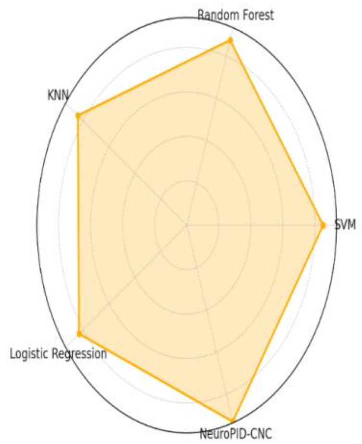

Figure 6: Recall comparison

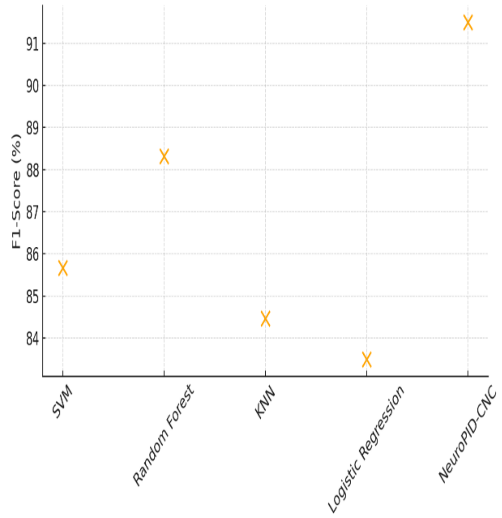

Figure 7: F1-Score comparison

From figure 6, the recall of proposed NeuroPID-CNC approach outperforms SVM, RF, KNN and LR by 9.24%, 6.16%, 10.71% and 11.91% respectively.

A high recall ensures that the model rarely overlooks true positive cases—an important feature in critical manufacturing scenarios where undetected deformations could jeopardize product quality, damage tools, or cause production downtime. This exceptional recall is due to the model's continuous feedback adjustment loop, inspired by the integral component of PID control, which improves detection sensitivity over time as more real-world machining data is processed. Figure 7 shows that NeuroPID-CNC has the best trade-off between precision and recall among all tested models, with an F1-score of 91.5%.

From figure 7, the F1-Score of proposed NeuroPID-CNC approach outperforms SVM, RF, KNN and LR by 6.81%, 3.60%, 8.32% and 9.58% respectively.

The F1-score, which is the harmonic mean of precision and recall, measures the model's overall effectiveness in handling the binary classification task. This balanced performance indicates that the NeuroPID-CNC model optimizes both false positives and false negatives, rather than favoring one over the other. Such a balance is critical in industrial settings where both unnecessary interventions and missed deformation risks have financial and operational implications. Finally, Figure 8 demonstrates that NeuroPID-CNC obtained the highest Matthews Correlation Coefficient (MCC) score of 0.84, which is widely considered one of the most reliable metrics for evaluating binary classifiers, especially on imbalanced datasets.

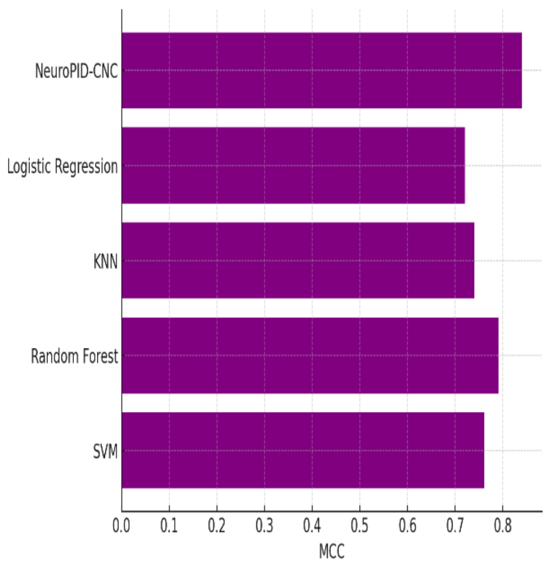

Figure 8: MCC comparison

From figure 8, the MCC of proposed NeuroPID-CNC approach outperforms SVM, RF, KNN and LR by 10.53%, 6.33%, 13.51% and 16.67% respectively.

MCC accounts for all four confusion matrix components (true positives, true negatives, false positives, and false negatives), providing a more complete picture of model performance. The high MCC score confirms that the model consistently and strongly correlates predicted and actual outcomes, regardless of class imbalance. This robust performance ensures reliability and fairness in prediction decisions over varying dataset distributions and machining conditions.

McNemar's test was employed to statistically validate the performance differences across classifiers based on the paired predictions of all models. Table 3 presents the results of the statistical significance test conducted with McNemar's test. The suggested method demonstrated statistically significant superiority over RF ($p < 0.001$), SVM ($p < 0.003$), KNN ($p=0.004$), and LR ($p<0.005$).

Table 3: Statistical Test - McNemar's Test

Algorithm	McNemar's statistic	p-value
SVM	42.13	0.002
RF	45.24	0.0001
KNN	39.18	0.004
LR	37.89	0.0045

4 Discussion

The single-neuron PID-inspired predictive control technique can surpass machine learning models such as RF, SVM, KNN, and LR. Single-neuron PID-inspired controllers are designed for dynamic system regulation, combining the advantages of PID control with adaptive features. It can adjust weights in real-time utilizing straightforward learning algorithms, rendering it suitable for dynamic, non-linear systems with fluctuating conditions. It provides a temporal viewpoint by evaluating past errors, the current state, and anticipated future behavior, which is consistent with control system needs. The methodology is interpretable, and its performance can be adjusted using domain expertise (e.g., calibrating proportional, integral, and derivative influences).

Machine learning algorithms are models trained in batches. They do not readily adapt in real time without expensive retraining. These are computationally intensive, perhaps rendering them unsuitable for real-time embedded control systems. It does not inherently manage temporal dynamics until augmented by time-lagged features, which may still lack responsiveness or interpretability.

The Single-Neuron PID-Inspired Control is proficient in real-time management of dynamic, nonlinear systems, adaptive error learning, feedback-based decision-making, and resource-constrained applications. The machine learning models exhibit challenges due to inadequate temporal feedback management, rigidity in online learning, elevated computational expenses (particularly in random forests and k-nearest neighbors), and limited adaptability in non-stationary control contexts.

The results demonstrate the superiority of the proposed NeuroPID-CNC model in predicting deformation risk during CNC machining. The model's PID-inspired single-neuron architecture not only provides superior performance across all standard classification metrics but it also ensures operational interpretability and real-time adaptability. These benefits make it an ideal candidate for smart manufacturing environments where precision, dependability, and responsiveness are crucial. Future research will concentrate on implementing the model on industrial edge devices for real-time inference, utilizing multi-modal sensor data including audio and thermal images, applying transfer learning for enhanced generalization, incorporating explainable AI methodologies to augment interpretability, and embedding the model within closed-loop control systems for autonomous CNC parameter modification based on predictive feedback.

5 Conclusion

This study described the NeuroPID-CNC algorithm, which is a lightweight single-neuron PID-inspired classifier for predicting deformation risk in CNC machining. The model outperformed traditional classifiers, achieving the highest accuracy, precision, recall, F1-score, and MCC, proving its suitability for real-time deformation risk detection and adaptive control in manufacturing. The current model was trained using data from a controlled lab environment, which may limit its applicability to different machine types and unstructured production scenarios. It also focuses solely on binary classification and requires manual feature selection, with no support for multi-output or continuous prediction tasks. Future research will focus on deploying the model on industrial edge devices for real-time inference, incorporating multi-modal sensor data such as audio and thermal images, using transfer learning for broader generalization, integrating explainable AI techniques to improve interpretability, and embedding the model into closed-loop control systems for autonomous CNC parameter adjustment based on predictive feedback.

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