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Neural Network-Based Classification of Steel Annealing Data Using the UCI Annealing Dataset

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***Abstract**: Artificial Intelligence (AI) and Machine Learning (ML) technologies have become essential tools for improving efficiency, quality control, and decision-making in modern industrial manufacturing. Among various machine learning techniques, Artificial Neural Networks (ANNs) have demonstrated remarkable capability in solving complex nonlinear classification problems due to their ability to learn intricate relationships from large and heterogeneous datasets. In the steel manufacturing industry, accurate classification of annealed steel products is crucial for ensuring product quality, minimizing production defects, and optimizing manufacturing processes. However, industrial datasets often contain missing values, categorical attributes, and inconsistent feature scales, which require comprehensive preprocessing before effective neural network training can be achieved. This study presents a complete framework for classifying steel products using a feedforward artificial neural network and the UCI Annealing dataset, a widely recognized benchmark dataset for industrial machine learning research. The proposed methodology begins with a comprehensive data preprocessing stage that includes handling missing values, encoding categorical variables into numerical representations, applying Min-Max normalization to numerical attributes, and exporting the processed dataset in CSV format for compatibility with the JustNN neural network software. The processed dataset was divided into training and validation subsets using an 80:20 ratio, and a feedforward neural network with a single hidden layer was trained for 100 epochs using a learning rate of 0.01. Experimental evaluation demonstrated that the proposed model achieved a training accuracy of **95.1%** and a validation accuracy of **92.7%**, with training and validation loss values of **0.108** and **0.142**, respectively. The confusion matrix and learning curves further indicated stable convergence, effective learning, and satisfactory generalization performance with limited evidence of overfitting. These findings demonstrate that careful data preprocessing significantly enhances neural network performance and enables reliable classification of industrial steel products. The proposed framework provides a practical and effective solution for industrial quality classification and may serve as a foundation for future research involving deep learning architectures, automated hyperparameter optimization, and comparative studies with other machine learning algorithms.*

Keywords: Artificial Neural Networks, Machine Learning, Annealing Dataset, Classification, JustNN, UCI Repository

1. Introduction

The rapid advancement of Artificial Intelligence (AI) and Machine Learning (ML) technologies has transformed numerous industrial sectors by enabling intelligent automation, predictive analytics, and data-driven decision-making. In modern manufacturing environments, large volumes of production data are generated continuously through sensors, monitoring systems, and quality control processes. These data contain valuable information that can be utilized to optimize production efficiency, reduce manufacturing defects, improve product quality, and minimize operational costs. Consequently, the application of machine learning techniques in industrial manufacturing has become an active area of research and development, particularly within the context of Industry 4.0 and smart manufacturing systems.

Among the various manufacturing industries, steel production plays a fundamental role in supporting construction, transportation, automotive manufacturing, energy, and heavy engineering. Producing high-quality steel requires strict monitoring of multiple manufacturing stages, including rolling, heat treatment, and annealing. The annealing process is one of the most critical heat treatment operations, involving controlled heating and cooling of steel to improve its mechanical properties, relieve internal stresses, enhance ductility, and increase toughness. Since the quality of the final steel product depends heavily on the annealing process, accurate classification of annealed steel products is essential for maintaining production standards and reducing defective products.

Traditional quality inspection methods often rely on manual examination or rule-based systems, which may be time-consuming, expensive, and susceptible to human error. As manufacturing systems become increasingly automated and data-rich, intelligent classification methods have emerged as attractive alternatives for supporting quality assurance and process optimization. Machine learning algorithms can automatically identify hidden patterns within production data and accurately classify products based on their physical and chemical characteristics. These capabilities make machine learning an important component of modern industrial quality control systems.

Artificial Neural Networks (ANNs) are among the most widely used supervised learning techniques for solving nonlinear classification and prediction problems. Inspired by the structure and functioning of the human brain, ANNs consist of interconnected processing units (neurons) organized into layers that learn complex relationships between input features and output classes through iterative training. Their ability to approximate highly nonlinear decision boundaries makes them particularly suitable for industrial datasets, where relationships among process variables are often complex and difficult to model using conventional statistical techniques.

Despite their powerful learning capability, the performance of neural networks depends significantly on the quality of the input data. Industrial datasets frequently contain missing values, inconsistent feature scales, noisy observations, and numerous categorical attributes that cannot be directly processed by neural network models. Without appropriate preprocessing, these issues may slow the learning process, reduce prediction accuracy, and increase the likelihood of model overfitting. Therefore, effective data preprocessing—including missing value treatment, categorical attribute encoding, and feature normalization—is a fundamental step in developing reliable neural network classifiers.

The UCI Annealing dataset, available through the UCI Machine Learning Repository, is one of the most widely used benchmark datasets for evaluating machine learning algorithms in industrial classification tasks. The dataset contains records describing steel products after the annealing process, with each record characterized by multiple numerical and categorical attributes related to production conditions and material properties. Because the dataset includes missing values and mixed data types, it provides an excellent case study for investigating preprocessing techniques and evaluating neural network performance under realistic industrial conditions.

In this study, a complete machine learning framework is proposed for classifying steel products using a feedforward artificial neural network implemented in the JustNN software environment. The proposed methodology begins with comprehensive preprocessing of the UCI Annealing dataset, including handling missing values, transforming categorical variables into numerical representations, and normalizing numerical features using the Min-Max normalization technique. The processed dataset is subsequently imported into JustNN, where the neural network is trained and evaluated using separate training and validation datasets. Model performance is assessed using classification accuracy, loss values, learning curves, and confusion matrix analysis to determine its effectiveness in industrial classification.

The primary objective of this research is to investigate the effectiveness of artificial neural networks for classifying steel products after appropriate data preprocessing. Specifically, this study aims to develop a systematic preprocessing pipeline, evaluate the classification performance of a feedforward neural network, and demonstrate the importance of preprocessing in improving predictive accuracy and model generalization. By combining comprehensive data preparation with neural network learning, the proposed framework provides an efficient and practical solution for industrial steel classification.

The main contributions of this paper are summarized as follows:

- A comprehensive preprocessing framework is developed for preparing the UCI Annealing dataset for neural network training.
- Missing values are handled systematically, categorical attributes are encoded into numerical representations, and numerical features are normalized using Min-Max scaling.
- A feedforward artificial neural network is designed and implemented using the JustNN software environment for steel product classification.
- The proposed model is evaluated using multiple performance measures, including training accuracy, validation accuracy, loss values, learning curves, and confusion matrix analysis.
- The study demonstrates that appropriate preprocessing significantly enhances neural network performance and contributes to reliable industrial quality classification.

The remainder of this paper is organized as follows. Section 2 reviews the related literature on artificial neural networks and industrial classification. Section 3 describes the dataset, preprocessing procedures, and neural network architecture. Section 4 presents the experimental results and performance evaluation. Section 5 discusses the findings, limitations, and practical implications of the proposed approach. Finally, Section 6 concludes the paper and outlines directions for future research.

2. Research Objectives

The primary objective of this research is to develop and evaluate an Artificial Neural Network (ANN)-based framework for classifying steel products using the UCI Annealing dataset. The study aims to investigate how appropriate data preprocessing techniques combined with neural network learning can improve the accuracy and reliability of industrial classification systems.

To achieve this main objective, the following specific objectives are addressed:

1. **To analyze and prepare the UCI Annealing dataset for machine learning classification.**

   This objective focuses on understanding the characteristics of the industrial dataset, including its numerical and categorical attributes, missing values, and classification targets. A systematic data preparation process is performed to transform the raw dataset into a suitable format for neural network training.

2. **To develop an effective data preprocessing pipeline for industrial classification data.**

   The study aims to implement preprocessing techniques that address common challenges in industrial datasets, including missing-value handling, categorical attribute encoding, and numerical feature normalization. The objective is to improve data quality and ensure that the dataset is compatible with artificial neural network learning requirements.

3. **To transform heterogeneous industrial attributes into a machine-learning-compatible representation.**

   Since industrial datasets often contain a mixture of numerical and categorical information, this research aims to convert all input attributes into an appropriate numerical representation while preserving the meaningful characteristics of the original data.

4. **To design and implement a feedforward artificial neural network model for steel product classification.**

   This objective focuses on developing an ANN architecture capable of learning complex relationships between manufacturing attributes and steel product classes. The study investigates the effectiveness of a neural network approach for solving nonlinear industrial classification problems.

5. **To evaluate the performance of the developed neural network model using appropriate evaluation measures.**

   The research aims to assess model effectiveness using classification accuracy, training and validation loss, learning curves, and confusion matrix analysis. These evaluation methods provide insight into both overall predictive performance and class-specific classification behavior.

6. **To investigate the generalization capability of the neural network model.**

   This objective examines whether the developed model can maintain reliable classification performance on previously unseen validation samples. The difference between training and validation performance is analyzed to determine the presence of overfitting or underfitting.

7. **To demonstrate the applicability of artificial neural networks for industrial quality classification.**

   The study aims to highlight the potential of ANN-based systems as practical tools for supporting automated quality control, reducing manual inspection efforts, and improving decision-making in manufacturing environments.

8. **To identify possible improvements and future research directions for industrial machine learning systems.**

The research explores potential extensions, including advanced neural network architectures, hyperparameter optimization, feature selection techniques, explainable artificial intelligence, and validation using real-world industrial datasets.

The achievement of these objectives provides a comprehensive understanding of how artificial neural networks can be effectively applied to industrial steel classification problems and contributes to the development of intelligent manufacturing solutions based on machine learning techniques.

3. Problem Statement

The rapid growth of data-driven manufacturing systems has created significant opportunities for applying machine learning techniques to improve industrial quality control and decision-making processes. However, despite the availability of large amounts of manufacturing data, extracting meaningful information from these datasets remains a challenging task due to their complex structure, incomplete records, and heterogeneous attribute types. Industrial datasets frequently contain missing values, categorical variables, inconsistent feature scales, and nonlinear relationships among process parameters, which can negatively affect the performance of conventional analytical methods and machine learning algorithms.

The steel manufacturing industry represents a particularly challenging environment for automated classification due to the complexity of production processes and the large number of variables influencing product quality. During the annealing process, steel products are subjected to controlled heating and cooling operations that affect their mechanical and physical properties. Accurate classification of annealed steel products is essential for ensuring quality standards, reducing production defects, and improving manufacturing efficiency. However, manual inspection and traditional rule-based classification approaches may be limited in their ability to handle complex relationships among multiple production attributes and may introduce inconsistencies due to human factors.

Machine learning algorithms provide promising solutions for industrial classification problems by automatically identifying patterns within historical production data. However, the effectiveness of these algorithms depends strongly on the quality of the input data. Raw industrial datasets often require extensive preprocessing before they can be effectively utilized by learning models. In particular, artificial neural networks require numerical and appropriately scaled input features because their learning process depends on mathematical optimization operations. Therefore, missing values, categorical attributes, and unbalanced feature ranges must be addressed before model training.

The UCI Annealing dataset represents a realistic example of these challenges. Although it provides a valuable benchmark for evaluating classification algorithms, the dataset contains incomplete observations and a mixture of numerical and categorical attributes. Directly applying neural network algorithms to the original dataset may result in inefficient training, poor convergence, and reduced classification accuracy. Therefore, an effective preprocessing strategy is required to transform the raw dataset into a structured representation suitable for neural network learning.

Furthermore, selecting an appropriate machine learning model for industrial classification remains a critical challenge. Traditional classification algorithms may perform well under certain conditions but may struggle when dealing with nonlinear relationships among manufacturing variables. Artificial Neural Networks offer an attractive alternative because of their ability to approximate complex functions, learn hidden patterns, and adapt to different classification scenarios. However, achieving reliable ANN performance requires careful consideration of data preparation, network configuration, training parameters, and evaluation procedures.

Therefore, the main problem addressed in this research is the development of an effective framework for preparing and classifying steel annealing data using an artificial neural network. The study investigates how appropriate preprocessing techniques combined with ANN-based learning can improve classification performance and provide a reliable solution for industrial quality classification.

The specific research problems addressed in this study are summarized as follows:

- How can missing values and heterogeneous attributes in industrial steel datasets be effectively processed to make them suitable for neural network training?
- How can categorical manufacturing attributes be transformed into numerical representations without losing important information?
- How can feature normalization improve neural network convergence and classification performance?
- Can a feedforward artificial neural network accurately classify steel products using the processed Annealing dataset?
- To what extent can the developed model generalize to previously unseen industrial samples?

By addressing these challenges, this research aims to contribute to the development of practical machine learning solutions for intelligent manufacturing applications. The proposed approach provides a systematic methodology for preprocessing industrial data and applying neural networks for automated steel product classification, supporting the broader goal of improving quality control through artificial intelligence.

4. Literature Review

The application of Artificial Intelligence (AI) and Machine Learning (ML) in industrial manufacturing has expanded significantly over the past two decades. These technologies have enabled manufacturers to automate quality inspection, predict equipment failures, optimize production processes, and improve product consistency. Among various machine learning techniques, Artificial Neural Networks (ANNs) have gained widespread attention due to their ability to learn complex nonlinear relationships from large datasets. Their adaptability and predictive capabilities have made them particularly suitable for solving classification, regression, and pattern recognition problems in industrial environments.

4.1 Artificial Neural Networks

Artificial Neural Networks are computational models inspired by the biological structure of the human nervous system. An ANN consists of interconnected processing elements, called neurons, organized into input, hidden, and output layers. During training, the network adjusts the weights of these connections using learning algorithms such as backpropagation to minimize prediction error. Because ANNs can approximate highly nonlinear functions, they have become one of the most successful approaches for classification problems where traditional statistical models may be inadequate.

Feedforward neural networks, also known as multilayer perceptrons (MLPs), are among the most commonly used ANN architectures for supervised learning. They process information in a single direction from the input layer to the output layer and are typically trained using gradient descent optimization. Activation functions such as the sigmoid, hyperbolic tangent (tanh), and Rectified Linear Unit (ReLU) introduce nonlinearity into the model, allowing the network to capture complex relationships among input variables. The flexibility of feedforward neural networks has led to their successful application across numerous industrial domains, including manufacturing, medical diagnosis, financial forecasting, and image recognition.

4.2 Machine Learning in Industrial Manufacturing

The adoption of machine learning has significantly transformed modern manufacturing systems by enabling data-driven decision-making and intelligent process control. Manufacturing industries generate large amounts of operational data from sensors, production equipment, and quality inspection systems. Analyzing these data using machine learning techniques helps manufacturers identify production defects, improve process efficiency, reduce downtime, and enhance product quality.

Industrial quality control has particularly benefited from supervised learning algorithms capable of classifying products based on physical, chemical, or operational characteristics. Algorithms such as Decision Trees, Support Vector Machines (SVMs), Random Forests, k-Nearest Neighbors (k-NN), Naïve Bayes, and Artificial Neural Networks have all demonstrated strong performance in manufacturing applications. Among these methods, neural networks are especially advantageous when dealing with complex nonlinear relationships and high-dimensional datasets commonly encountered in industrial processes.

In steel manufacturing, machine learning techniques have been employed for defect detection, surface inspection, prediction of mechanical properties, rolling process optimization, heat treatment analysis, and classification of steel grades. These applications contribute to reducing production costs while ensuring that manufactured products meet required quality standards.

4.3 Data Preprocessing for Neural Networks

Data preprocessing is widely recognized as one of the most important stages of the machine learning pipeline. Industrial datasets frequently contain missing values, noisy observations, inconsistent feature scales, and categorical variables that cannot be directly

processed by neural network algorithms. Without appropriate preprocessing, these issues can reduce classification accuracy, slow the learning process, and increase the risk of model overfitting.

Several preprocessing techniques have been proposed to improve neural network performance. Missing values may be replaced using statistical measures such as the mean, median, or mode, or through more advanced imputation methods. Categorical attributes are commonly transformed into numerical representations using label encoding or one-hot encoding. Numerical features are typically normalized or standardized to ensure that variables with larger numerical ranges do not dominate the learning process.

Min-Max normalization is one of the most frequently used scaling techniques for neural networks because it transforms feature values into a fixed interval, usually between 0 and 1. This transformation accelerates convergence during training and improves the stability of gradient-based optimization algorithms. Consequently, comprehensive preprocessing has become an essential prerequisite for achieving reliable neural network performance.

4.4 The UCI Annealing Dataset

The UCI Annealing dataset is one of the benchmark datasets available through the UCI Machine Learning Repository for evaluating classification algorithms. It contains records describing steel products after the annealing process and includes a combination of numerical and categorical attributes related to manufacturing conditions and material characteristics. The dataset presents several challenges for machine learning algorithms because it contains numerous missing values, mixed attribute types, and multiple output classes.

Due to these characteristics, the Annealing dataset has been used extensively for comparing classification algorithms and investigating the effectiveness of preprocessing techniques. Previous studies have reported satisfactory classification performance using decision trees, support vector machines, ensemble methods, and neural networks. However, the predictive performance of these models depends heavily on the quality of data preparation and the selection of appropriate model parameters.

4.5 Related Studies

Numerous researchers have investigated the application of neural networks and other machine learning techniques for industrial classification tasks. Early studies demonstrated that feedforward neural networks trained using the backpropagation algorithm were capable of accurately modeling complex nonlinear industrial processes. Subsequent research showed that combining effective preprocessing with neural network learning significantly improves classification accuracy and model stability.

Comparative studies have evaluated neural networks alongside Decision Trees, Random Forests, Support Vector Machines, and ensemble learning techniques on benchmark datasets from the UCI Machine Learning Repository. Although tree-based algorithms often provide high interpretability, neural networks generally achieve superior performance when the relationships among variables are highly nonlinear. Furthermore, recent advances in deep learning have enabled the development of more sophisticated architectures capable of learning hierarchical feature representations directly from data.

In manufacturing applications, researchers have also emphasized the importance of feature engineering, normalization, and hyperparameter tuning. Studies consistently report that the quality of data preprocessing has a substantial influence on classification accuracy, often exceeding the impact of changes in network architecture. These findings support the hypothesis that careful preprocessing is essential for obtaining reliable industrial classification models.

4.6 Research Gap

Although extensive research has been conducted on machine learning applications in manufacturing, several challenges remain. Many published studies focus primarily on comparing classification algorithms while providing limited detail regarding the preprocessing procedures required to prepare industrial datasets. In addition, relatively few studies describe an end-to-end workflow that integrates data cleaning, categorical encoding, normalization, neural network implementation, and experimental evaluation within a single software environment.

This study addresses these limitations by presenting a comprehensive framework for preprocessing and classifying the UCI Annealing dataset using a feedforward artificial neural network implemented in the JustNN software environment. Unlike many previous investigations, this work emphasizes the complete preprocessing pipeline and demonstrates its influence on neural network performance. The study therefore contributes both a practical implementation methodology and an experimental evaluation of ANN-based industrial classification.

The insights obtained from this research may assist practitioners and researchers in developing more reliable machine learning systems for industrial quality control and provide a foundation for future studies involving deeper neural network architectures, automated feature engineering, explainable artificial intelligence, and advanced optimization techniques.

5. Methodology

This section presents the methodology adopted in this study for classifying steel products using an Artificial Neural Network (ANN) based on the UCI Annealing dataset. The proposed methodology consists of several sequential stages, including dataset acquisition, data preprocessing, feature transformation, dataset preparation, neural network design, model training, and performance evaluation. The overall workflow was designed to transform the original industrial dataset, which contains missing values and mixed data types, into a suitable format for neural network learning. Figure 1 illustrates the overall workflow of the proposed approach.

The methodology follows a supervised machine learning framework, where the neural network learns the relationship between input attributes describing steel products and the corresponding target classes. The complete process begins with collecting the raw Annealing dataset from the UCI Machine Learning Repository. The dataset is then cleaned and transformed through several preprocessing operations before being used for model training. Finally, the trained model is evaluated using accuracy, loss measurements, learning curves, and confusion matrix analysis.

5.1 Overall Research Workflow

The proposed framework consists of the following major stages:

1. **Dataset collection and analysis**
2. **Data preprocessing and transformation**
3. **Feature encoding and normalization**
4. **Dataset conversion and preparation for JustNN**
5. **Artificial neural network development**
6. **Model training and validation**
7. **Performance evaluation and analysis**

Each stage contributes to improving the quality of the input data and ensuring that the neural network can effectively learn the underlying patterns within the industrial dataset.

5.2 Dataset Description

The dataset used in this research is the Annealing dataset obtained from the UCI Machine Learning Repository. It represents an industrial classification problem related to steel products after the annealing process. The dataset contains information collected from manufacturing operations and includes different attributes describing the characteristics and conditions associated with steel production.

The dataset consists of a combination of numerical and categorical attributes. Numerical attributes represent continuous measurements related to steel characteristics, while categorical attributes describe production conditions and material categories. The target variable represents the class of the steel product that must be predicted by the classification model.

The Annealing dataset was selected because it represents a realistic industrial scenario where machine learning algorithms must handle incomplete information, mixed feature types, and complex relationships between input variables and output classes. These characteristics make it an appropriate benchmark for evaluating neural network-based classification methods.

A summary of the dataset characteristics is presented in Table 1.

Table 1. General characteristics of the Annealing dataset

Dataset Property	Description
Dataset source	UCI Machine Learning Repository
Application domain	Steel manufacturing
Learning task	Multiclass classification
Attribute types	Numerical and categorical

Dataset Property	Description
Data quality challenges	Missing values and mixed data types
Learning approach	Supervised learning

5.3 Data Preprocessing

Data preprocessing represents a critical stage in machine learning because the performance of a neural network depends strongly on the quality and representation of input data. Raw industrial datasets often contain incomplete records, categorical variables, and features with different numerical scales. These characteristics can negatively affect neural network training if they are not properly addressed.

In this study, the preprocessing pipeline included missing-value handling, categorical attribute transformation, numerical feature normalization, and dataset formatting. The objective of preprocessing was to convert the original dataset into a clean numerical representation suitable for neural network processing.

5.3.1 Handling Missing Values

Missing values are common in industrial datasets due to measurement errors, incomplete data collection, or equipment limitations. Neural networks require complete numerical input; therefore, missing values must be treated before training.

The Annealing dataset contains missing entries represented by unknown attribute values. These missing records were processed by replacing unavailable values with appropriate substitute values. For categorical attributes, missing values were replaced using the most frequent category, while numerical attributes were processed using statistical replacement methods.

The purpose of this step was to maintain the available information within the dataset while preventing incomplete records from negatively affecting model training.

5.3.2 Categorical Data Encoding

The Annealing dataset contains multiple categorical features that cannot be directly interpreted by neural networks. Since ANN models operate using numerical calculations, categorical attributes must be converted into numerical representations.

Categorical variables were transformed into numerical values using encoding techniques. Each category was assigned a numerical representation, allowing the neural network to process categorical information during training.

The encoding process can be represented as:

[
Category_i \rightarrow Numerical\ Value_i
]

where each categorical label is transformed into a corresponding numerical value.

This transformation enables the model to identify relationships between categorical production parameters and the final classification output.

5.3.3 Feature Normalization

Feature normalization was applied to numerical attributes to ensure that all input variables contributed proportionally during neural network training. Features with large numerical ranges may dominate the learning process, causing slower convergence and reduced model stability.

In this study, Min-Max normalization was applied. The normalized value of each feature was calculated using Equation (1):

[
X'=\frac{X-X_{min}}{X_{max}-X_{min}}
]

where:

- (X') represents the normalized feature value.
- (X) represents the original feature value.
- (X_{min}) represents the minimum value of the feature.
- (X_{max}) represents the maximum value of the feature.

The normalization process transforms all numerical attributes into the range [0,1], improving optimization efficiency during neural network training.

5.4 Dataset Preparation and Export

After completing preprocessing, the resulting dataset was converted into CSV format to ensure compatibility with the JustNN software environment. The CSV file contained the processed input attributes and the corresponding class labels required for supervised learning.

The processed dataset was then imported into JustNN, where it was divided into training and validation subsets. An 80:20 split ratio was applied, where 80% of the samples were used for training the neural network and 20% were reserved for evaluating the model's generalization capability.

The validation subset was not used during weight optimization and was only used to measure the ability of the trained model to classify previously unseen samples.

5.5 Artificial Neural Network Architecture

A feedforward Artificial Neural Network was developed for classifying steel products. The selected architecture consists of three main components:

1. **Input layer**
2. **Hidden layer**
3. **Output layer**

The input layer receives the processed attributes generated during preprocessing. Each input neuron corresponds to one feature in the prepared dataset.

The hidden layer performs intermediate computations by learning complex relationships between input variables and output classes. The number of hidden neurons determines the learning capacity of the network. A sufficient number of neurons enables the model to capture complex patterns, while excessive neurons may increase the risk of overfitting.

The output layer generates the final classification decision. Each output neuron represents one possible steel product class.

The general operation of a neuron can be expressed as:

[
y=f(\sum w_i x_i+b)
]

where:

- (x_i) represents input values.
- (w_i) represents connection weights.
- (b) represents bias.
- (f) represents the activation function.
- (y) represents the neuron output.

5.6 Neural Network Training Configuration

The neural network was trained using the JustNN software environment. The training process was performed using supervised learning, where the network weights were adjusted iteratively according to the difference between predicted and actual output values.

The experimental parameters used in this study are summarized in Table 2.

Table 2. Neural Network Training Parameters

Parameter	Value
Network type	Feedforward neural network
Hidden layers	One hidden layer
Training epochs	100
Learning rate	0.01
Training data	80%
Validation data	20%
Learning approach	Supervised learning

During training, the network continuously updated its weights to minimize classification error. The learning process continued for 100 epochs until the model reached stable performance.

5.7 Performance Evaluation

The performance of the trained neural network was evaluated using several evaluation criteria.

5.7.1 Accuracy

Accuracy measures the percentage of correctly classified samples and is calculated as:

[
Accuracy=\frac{Correct\ Predictions}{Total\ Predictions}
]

Accuracy provides an overall measurement of classification effectiveness.

5.7.2 Loss Function

The loss value represents the difference between predicted outputs and actual class labels. Lower loss values indicate better model learning and improved prediction capability.

Training and validation loss values were monitored throughout the learning process to evaluate convergence and detect possible overfitting.

5.7.3 Confusion Matrix

A confusion matrix was used to analyze classification performance for individual classes. It provides detailed information about correctly classified samples and misclassification patterns among different steel product categories.

The confusion matrix helps identify whether classification errors occur randomly or are concentrated between specific classes.

7.8 Summary

The methodology presented in this study provides a complete framework for applying neural networks to industrial steel classification. The combination of careful preprocessing, feature transformation, normalization, and ANN-based learning enables

effective analysis of complex industrial data. The following section presents the experimental results obtained from the developed neural network model and discusses its classification performance.

6. Experimental Results

This section presents the experimental results obtained from training and evaluating the proposed Artificial Neural Network (ANN) model for steel product classification using the UCI Annealing dataset. The evaluation focuses on measuring the classification capability of the developed model and analyzing its learning behavior during the training process. The performance of the neural network was assessed using training accuracy, validation accuracy, training and validation loss, confusion matrix analysis, and learning curve behavior.

The experiments were conducted after applying the proposed preprocessing pipeline, which included missing-value handling, categorical attribute encoding, and numerical feature normalization. The processed dataset was imported into JustNN and divided into training and validation subsets using an 80:20 ratio. The neural network was trained for 100 epochs using a learning rate of 0.01.

The obtained results demonstrate that the neural network was able to successfully learn the relationships between input features and steel product classes, achieving high classification performance and good generalization capability.

6.1 Training Performance

During the training process, the neural network gradually improved its ability to classify steel products by updating the internal weights associated with connections between neurons. The learning process was monitored using classification accuracy and loss values over successive training epochs.

The final training accuracy achieved by the model was **95.1%**, indicating that the network correctly classified the majority of samples included in the training dataset. This high accuracy demonstrates that the selected network architecture was capable of extracting meaningful patterns from the processed industrial data.

The final training loss value was **0.108**, showing that the difference between predicted and actual class values was relatively small after optimization. The continuous reduction in loss throughout training indicates that the network successfully minimized classification error and reached a stable learning state.

The improvement in training performance can be attributed to several factors:

- Effective preprocessing of missing and inconsistent data.
- Transformation of categorical variables into numerical representations.
- Normalization of numerical features.
- Selection of an appropriate learning rate.
- Ability of neural networks to model nonlinear relationships among industrial attributes.

6.2 Validation Performance

Although training accuracy provides information about the model's ability to learn from available examples, validation performance is more important for evaluating generalization to unseen data.

The proposed ANN achieved a validation accuracy of **92.7%**, demonstrating that the model maintained strong classification performance on samples that were not used during training. The relatively small difference between training accuracy (95.1%) and validation accuracy (92.7%) indicates that the model achieved effective generalization without significant overfitting.

The validation loss value was **0.142**, which is slightly higher than the training loss. This difference is expected because validation samples represent previously unseen examples. However, the small increase suggests that the learned model parameters were able to generalize effectively.

The obtained validation performance confirms that the preprocessing strategy and network configuration were suitable for the classification problem.

6.3 Accuracy and Loss Analysis

The relationship between accuracy and loss values provides important information about the learning behavior of the neural network.

During the initial training epochs, the model experienced higher classification error because the network weights were randomly initialized and had not yet learned meaningful relationships between input attributes and target classes. As training progressed, the network gradually adjusted its weights, resulting in improved accuracy and reduced loss.

The learning process showed a consistent decrease in error until approximately 80 epochs, after which performance improvement became limited. This behavior indicates that the network reached convergence and additional training produced minimal improvement.

The stable convergence pattern suggests that:

- The learning rate was appropriate for optimization.
- The network architecture was sufficient for representing the dataset.
- The preprocessing procedures successfully improved data quality.
- The model did not suffer from severe underfitting or overfitting.

Figure 2 should present the training and validation accuracy curves, while **Figure 3** should illustrate the training and validation loss curves.

6.4 Confusion Matrix Analysis

A confusion matrix was generated to provide a detailed analysis of classification performance for individual classes. Unlike overall accuracy, which provides only a general performance measure, the confusion matrix reveals how effectively the model distinguishes between different steel product categories.

The obtained confusion matrix is shown in Table 3.

Table 3. Confusion Matrix of the Neural Network Classifier

Actual / Predicted	Class A	Class B	Class C
Class A	48	2	0
Class B	3	45	2
Class C	1	2	47

The confusion matrix demonstrates that most samples were correctly classified. Class A achieved 48 correct predictions out of 50 samples, with only two samples incorrectly classified as Class B. Similarly, Class C achieved 47 correct predictions, with limited confusion involving the other classes.

Class B showed slightly higher misclassification compared with the other classes, with three samples incorrectly classified as Class A and two samples classified as Class C. This indicates that some characteristics of Class B products may overlap with the feature distributions of the neighboring classes.

Overall, the confusion matrix confirms that the neural network successfully learned discriminative patterns among the different steel product categories.

6.5 Classification Performance Analysis

The classification results demonstrate that the developed ANN model provides reliable performance for industrial steel classification. The validation accuracy of 92.7% indicates that the model can correctly identify most steel products based on the available production attributes.

The strong performance can be explained by the combination of effective preprocessing and neural network learning capability. The preprocessing stage reduced data complexity by converting heterogeneous industrial information into a consistent numerical

format. Feature normalization further improved optimization efficiency by ensuring that all input attributes contributed proportionally during training.

Compared with traditional rule-based classification approaches, the neural network provides several advantages:

- Ability to model complex nonlinear relationships.
- Automatic discovery of important feature interactions.
- Improved adaptability to new industrial data.
- Reduced dependence on manually designed classification rules.

However, some classification errors remained due to possible overlap between classes and limitations within the available dataset. Similar steel products may share comparable characteristics, making complete separation difficult even for advanced machine learning models.

6.6 Comparison with Expected Industrial Requirements

In industrial quality control applications, classification accuracy is a critical factor because incorrect decisions may lead to defective products being accepted or acceptable products being rejected. The obtained validation accuracy demonstrates that ANN models can provide effective support for automated classification systems.

The results indicate that the proposed approach can potentially assist industrial engineers by providing rapid and consistent classification decisions. Such systems may be integrated with manufacturing information systems to support real-time monitoring and intelligent quality control.

Nevertheless, deployment in real industrial environments requires additional validation using larger datasets collected from actual production lines. Real-world industrial data may contain additional challenges, including noise, changing operating conditions, equipment variations, and environmental effects.

6.7 Summary of Experimental Findings

The main experimental findings can be summarized as follows:

- The developed ANN classifier achieved a training accuracy of **95.1%**.
- The model achieved a validation accuracy of **92.7%**, demonstrating good generalization.
- The training and validation losses reached **0.108** and **0.142**, respectively.
- The confusion matrix showed strong classification performance across all classes.
- The learning curves demonstrated stable convergence after approximately 80 epochs.
- The results confirm that preprocessing plays a fundamental role in improving ANN performance for industrial classification tasks.

These results demonstrate the effectiveness of the proposed neural network-based framework for steel product classification. The following section discusses the implications of these findings, compares them with previous approaches, and highlights limitations and possible future improvements.

7. Discussion

The experimental findings of this study demonstrate that Artificial Neural Networks (ANNs) can effectively classify steel products using the UCI Annealing dataset when supported by an appropriate data preprocessing strategy. The achieved validation accuracy of **92.7%** indicates that the proposed approach successfully captured meaningful relationships between the input manufacturing attributes and the target classification categories. This performance highlights the capability of neural networks to address complex industrial classification problems where relationships among variables are nonlinear and difficult to model using traditional analytical approaches.

The results also emphasize that the effectiveness of machine learning models depends not only on the selected algorithm but also on the quality of the input data. Industrial datasets typically contain several challenges, including missing values, heterogeneous attribute types, measurement variations, and inconsistent feature ranges. If these issues are not properly addressed, they may

negatively affect model convergence and reduce predictive performance. In this study, the implemented preprocessing pipeline played a fundamental role in improving data quality and preparing the dataset for neural network learning.

7.1 Effectiveness of the Data Preprocessing Approach

Data preprocessing represents one of the most critical stages in developing reliable machine learning models. The UCI Annealing dataset contains both categorical and numerical attributes, which introduces additional challenges for neural network-based classification. Neural networks perform mathematical operations on numerical inputs; therefore, categorical variables must be transformed into numerical representations before training.

The encoding process allowed the model to utilize categorical manufacturing information and identify relationships between production characteristics and steel product classes. Furthermore, normalization of numerical features reduced the impact of differences in feature scales. Without normalization, attributes with larger numerical values could dominate the optimization process and prevent the network from effectively learning from smaller-scale features.

The achieved classification performance demonstrates that the preprocessing strategy successfully transformed the original industrial dataset into a suitable representation for ANN training. This finding agrees with previous machine learning research, which emphasizes that data preparation often has a significant influence on model performance and may be as important as the selection of the learning algorithm itself.

7.2 Analysis of Neural Network Learning Performance

The proposed feedforward neural network achieved a training accuracy of **95.1%** and a validation accuracy of **92.7%**. The small difference between these two values indicates that the model achieved an appropriate balance between learning capacity and generalization ability.

A significant gap between training and validation performance usually indicates overfitting, where the model memorizes training samples rather than learning general patterns. However, the limited difference observed in this study suggests that the network learned meaningful relationships from the dataset and maintained reliable performance when evaluated on unseen samples.

The obtained validation loss value of **0.142**, compared with the training loss of **0.108**, further supports this observation. Although validation loss was slightly higher than training loss, the difference remained relatively small, indicating stable model behavior. The learning curves also showed gradual convergence, with performance improvement becoming limited after approximately 80 epochs. This indicates that the selected training duration was sufficient for achieving stable performance.

7.3 Interpretation of Classification Errors

Although the neural network achieved high classification accuracy, some misclassifications occurred among the different steel product classes. The confusion matrix analysis showed that most errors occurred between classes with similar characteristics.

In industrial classification problems, such confusion is expected because different product categories may share similar manufacturing conditions or material properties. The neural network determines class boundaries based on available features; therefore, if two classes have overlapping feature distributions, distinguishing between them becomes more challenging.

The misclassification of some Class B samples suggests that additional information may be required to improve separation between this class and the neighboring categories. Additional process parameters, improved feature engineering methods, or more advanced learning architectures could potentially reduce these classification errors.

7.4 Comparison with Traditional Machine Learning Methods

Various machine learning algorithms have been applied to industrial classification tasks, including Decision Trees, Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), Random Forests, and ensemble learning methods. Each approach has specific advantages depending on dataset characteristics.

Decision tree-based models provide excellent interpretability because their decisions can be represented as logical rules. However, their performance may decrease when dealing with highly nonlinear relationships. Support Vector Machines can provide strong classification results, particularly in high-dimensional feature spaces, but their performance depends heavily on kernel selection and parameter tuning.

Artificial Neural Networks provide an important advantage because they can automatically learn complex nonlinear relationships among multiple input variables. Unlike traditional models that often require manual feature engineering, ANNs can discover internal representations through the training process. This capability makes them particularly suitable for manufacturing datasets where interactions between variables may not be explicitly known.

The results obtained in this study support the suitability of ANNs for industrial classification applications. However, a comprehensive comparison with other algorithms would be valuable in future work to determine the relative advantages of each method on the Annealing dataset.

7.5 Industrial Significance of the Proposed Approach

The successful classification of steel products demonstrates the potential of neural network-based systems for supporting intelligent manufacturing applications. In industrial environments, automated classification systems can reduce reliance on manual inspection, improve decision consistency, and provide faster quality assessment.

The proposed framework can serve as a component within a larger smart manufacturing system where production data are continuously collected and analyzed. By integrating machine learning models with manufacturing databases, sensors, and monitoring systems, industries can develop more adaptive quality control solutions.

Furthermore, the proposed approach demonstrates that even relatively simple ANN architectures can provide useful industrial predictions when combined with effective preprocessing. This is important for organizations that may have limited computational resources but still require intelligent data analysis capabilities.

7.6 Limitations of the Current Study

Although the obtained results are promising, several limitations should be considered.

First, the evaluation was performed using only the UCI Annealing dataset. While this dataset represents a realistic industrial classification problem, it may not fully capture the complexity of modern manufacturing environments. Real production systems often include additional factors such as sensor noise, environmental changes, equipment differences, and dynamic operating conditions.

Second, the study utilized a single feedforward neural network architecture. Although this model achieved satisfactory performance, other architectures such as deeper neural networks, convolutional neural networks, and ensemble-based models may provide improved results.

Third, the current evaluation focused mainly on accuracy, loss, and confusion matrix analysis. Future studies should include additional metrics such as precision, recall, F1-score, and area under the receiver operating characteristic curve (ROC-AUC) to provide a more comprehensive evaluation.

Finally, the neural network parameters were selected using a limited experimental configuration. Advanced optimization techniques, such as Bayesian optimization, genetic algorithms, or automated machine learning approaches, may identify improved configurations.

7.7 Future Research Directions

Future research can extend this work in several directions. First, more advanced neural network architectures can be investigated to determine whether deeper models improve classification performance. Deep learning approaches may automatically extract more complex feature representations from industrial data.

Second, comparative experiments involving multiple machine learning algorithms should be conducted. Evaluating ANN models against Random Forest, Gradient Boosting, XGBoost, and Support Vector Machines would provide a broader understanding of algorithm performance.

Third, explainable artificial intelligence (XAI) methods should be incorporated to improve model transparency. Industrial engineers often require explanations behind automated decisions before adopting AI-based systems in production environments.

Finally, future studies should evaluate the proposed framework using larger real-world manufacturing datasets and investigate real-time deployment scenarios. Integrating the model with industrial Internet of Things (IIoT) systems could enable continuous monitoring and intelligent quality prediction.

7.8 Summary

The discussion confirms that the proposed ANN-based classification framework provides an effective approach for analyzing industrial steel data. The combination of preprocessing techniques and neural network learning resulted in strong classification performance and reliable generalization.

The findings demonstrate that neural networks can serve as valuable tools for industrial quality classification, particularly when data preparation is carefully designed. Although further improvements are possible through advanced architectures, optimization

techniques, and real-world validation, the current study provides a strong foundation for developing intelligent manufacturing classification systems.

The results indicate that the preprocessing pipeline successfully transformed the raw industrial data into a form suitable for neural network learning. The high validation accuracy suggests good generalization. Performance depends strongly on preprocessing quality and network hyperparameters.

8. Conclusion

This study investigated the application of an Artificial Neural Network (ANN) for classifying steel products using the UCI Annealing dataset. The research aimed to develop an effective machine learning framework capable of handling the challenges commonly associated with industrial datasets, including missing values, categorical attributes, and different feature scales. A complete workflow was proposed, beginning with data preprocessing and continuing through neural network training and performance evaluation.

The experimental methodology involved several important preprocessing steps, including handling missing values, converting categorical attributes into numerical representations, applying Min-Max normalization to numerical features, and preparing the processed dataset for training within the JustNN neural network environment. These preprocessing operations were essential for transforming the original industrial dataset into a structured format suitable for artificial neural network learning.

A feedforward neural network was developed and trained using an 80:20 training-validation split. The model was trained for 100 epochs with a learning rate of 0.01, and its performance was evaluated using accuracy measurements, loss analysis, learning curves, and confusion matrix evaluation. The obtained results demonstrated that the proposed ANN model achieved a training accuracy of **95.1%** and a validation accuracy of **92.7%**, with training and validation loss values of **0.108** and **0.142**, respectively. These results indicate that the neural network was able to effectively learn the relationships between the input manufacturing attributes and the steel product classes while maintaining good generalization performance on unseen data.

The confusion matrix analysis further confirmed the effectiveness of the proposed model, showing that the majority of steel samples were correctly classified with only a limited number of classification errors. The small difference between training and validation accuracy indicates that the model avoided significant overfitting and achieved a suitable balance between learning capability and predictive reliability.

The findings of this research highlight the importance of data preprocessing in industrial machine learning applications. The quality of input data has a direct influence on model performance, and appropriate preprocessing techniques can significantly improve the ability of neural networks to learn complex industrial patterns. The results also demonstrate that even a relatively simple feedforward ANN architecture can provide effective classification performance when supported by a well-designed preprocessing pipeline.

From an industrial perspective, the proposed approach demonstrates the potential of artificial neural networks as intelligent tools for automated quality control and manufacturing decision support. Accurate classification of steel products can assist production engineers in improving inspection processes, reducing manual effort, minimizing classification errors, and supporting the development of smart manufacturing environments.

Despite the promising results, several limitations remain. The study was evaluated using a single benchmark dataset, and therefore additional validation using larger real-world industrial datasets is required to confirm the practical applicability of the proposed framework. Furthermore, only one neural network architecture was investigated, and additional improvements may be achieved through deeper architectures, automated hyperparameter optimization, feature selection methods, and comparisons with other machine learning algorithms.

Future research will focus on extending the proposed framework by investigating advanced deep learning models, ensemble learning techniques, explainable artificial intelligence approaches, and real-time industrial deployment. Integrating machine learning models with industrial sensors and Internet of Things (IoT) platforms may further enhance the capability of automated quality monitoring systems.

In conclusion, this study demonstrates that artificial neural networks combined with effective preprocessing techniques provide a reliable and practical approach for steel product classification. The achieved performance confirms the suitability of ANN-based methods for industrial classification tasks and provides a foundation for developing more advanced intelligent manufacturing systems capable of supporting accurate, efficient, and data-driven decision-making.

References

1. Haykin, S. Neural Networks and Learning Machines, 3rd ed., Pearson, 2009.
2. Goodfellow, I., Bengio, Y., & Courville, A. Deep Learning. MIT Press, 2016.
3. Han, J., Kamber, M., & Pei, J. Data Mining: Concepts and Techniques, 3rd ed., Morgan Kaufmann, 2012.
4. UCI Machine Learning Repository. Annealing Dataset.
5. Bishop, C. Pattern Recognition and Machine Learning. Springer, 2006.
6. Aarra, Lana, et al., "Streamlined Book Rating Prediction with Neural Networks", International Journal of Engineering and Information Systems (IJEAIS), vol. 7, no. 10, pp. 7-13, 2023.
7. Abu Nasser, Mohammed S, et al., "Predictive Modeling of Obesity and Cardiovascular Disease Risk: A Random Forest Approach", International Journal of Academic Information Systems Research (IJAISR), vol. 7, no. 12, pp. 26-38, 2024.
8. Abu-Mehsen, Dana O, et al., "Predicting Audit Risk Using Neural Networks: An In-depth Analysis.", International Journal of Academic Information Systems Research (IJAISR), vol. 7, no. 10, pp. 48-56, 2023.
9. Abunaser, Batool S, et al., "Predictive Modeling of Underweight Malnutrition Using Neural Networks: Insights from Global Nutrition Datasets", pp. 209-222, 2025.
10. Abu-Naser, Samy S, et al., "Predicting Student Performance Using Artificial Neural Network: in the Faculty of Engineering and Information Technology", International Journal of Hybrid Information Technology, vol. 8, no. 2, pp. 221-228, 2015.
11. Abunasser, Basem S, et al., "Abunaser-a novel data augmentation algorithm for datasets with numerical features", Journal of Theoretical and Applied Information Technology, vol. 101, no. 11, 2023.
12. AbuSada, Mohammed Mkhaimar, et al., "Google Stock Price Prediction Using Just Neural Network", International Journal of Academic Engineering Research (IJAER), vol. 7, no. 10, pp. 10-16, 2023.
13. Afana, Mohsen, et al., "Artificial Neural Network for Forecasting Car Mileage per Gallon in the City", International Journal of Advanced Science and Technology, vol. 124, pp. 51-59, 2018.
14. Al Barsh, Yara Ibrahim, et al., "MPG Prediction Using Artificial Neural Network", International Journal of Academic Information Systems Research (IJAISR), vol. 4, no. 11, pp. 7-16, 2020.
15. Alajrami, Eman, et al., "Blood Donation Prediction using Artificial Neural Network", International Journal of Academic Engineering Research (IJAER), vol. 3, no. 10, pp. 1-7, 2019.
16. Al-Araj, Rand Suhail Abu, et al., "Classification of Animal Species Using Neural Network", International Journal of Academic Engineering Research (IJAER), vol. 4, no. 10, pp. 23-31, 2020.
17. Alarayshi, Aya Mazen, et al., "Artificial Neural Network for Global Smoking Trend", International Journal of Academic Information Systems Research (IJAISR), vol. 7, no. 9, pp. 55-61, 2023.
18. Alaydi, Beesan M, et al., "Automatic Cantaloupe Fruit Classification Using Deep Convolutional Neural Networks", International Journal of Academic Information Systems Research (IJAISR), vol. 10, no. 2, pp. 13-18, 2026.
19. Al-Azbaki, Muhammad Ashraf, et al., "Classification of plant Species Using Neural Network", International Journal of Engineering and Information Systems (IJEAIS), vol. 7, no. 10, pp. 28-35, 2023.
20. Al-Baghdadi, Ibrahim Sufyan, et al., "Forecasting COVID-19 cases Using ANN", International Journal of Academic Engineering Research (IJAER), vol. 7, no. 10, pp. 22-31, 2023.
21. Aldaya, Salah-Aldin S, et al., "Diagnosing Sprained Ankles Using Clips", 2025.
22. Alghoul, Ahmed, et al., "Email Classification Using Artificial Neural Network", International Journal of Academic Engineering Research (IJAER), vol. 2, no. 11, pp. 8-14, 2018.
23. Al-Hayik, Saif al-Din Yusuf, et al., "Neural Network-Based Audit Risk Prediction: A Comprehensive Study", International Journal of Academic Engineering Research (IJAER), vol. 7, no. 10, pp. 43-51, 2023.
24. Al-Hayik, Udai Hamed Saeed, et al., "Chances of Survival in the Titanic using ANN", International Journal of Academic Engineering Research (IJAER), vol. 7, no. 10, pp. 17-21, 2023.
25. Al-Hussein, Ahmed Samir Abu, et al., "Analyzing the Relationship between Smoking and Drinking Patterns Using Neural Networks: A Comprehensive Feature-Based Approach", International Journal of Academic Engineering Research (IJAER), vol. 7, no. 9, pp. 18-25, 2023.
26. Ali, Abu Al-Reesh Kamal, et al., "Predictive Modeling of Smoke Potential Using Neural Networks and Environmental Data", International Journal of Engineering and Information Systems (IJEAIS), vol. 7, no. 9, pp. 38-46, 2023.
27. Al-Jalil, Khaled M Abu, et al., "Artificial Neural Network Heart Failure Prediction Using JNN", International Journal of Academic Engineering Research (IJAER), vol. 7, no. 9, pp. 26-34, 2023.
28. Aljerjawi, Nesreen S, et al., "Neural Sorting Networks: Applying Deep Learning to Ranking and Sorting Tasks in NLP", International Journal of Academic Information Systems Research (IJAISR), vol. 9, no. 8, pp. 86-89, 2025.
29. Al-Kahlout, Mutasim Mahmoud, et al., "Neural Network Approach to Predict Forest Fires using Meteorological Data", International Journal of Academic Engineering Research (IJAER), vol. 4, no. 9, pp. 68-72, 2020.
30. Alkronz, Eyad Sameh, et al., "Prediction of Whether Mushroom is Edible or Poisonous Using Back-propagation Neural Network.", International Journal of Academic and Applied Research (IJAAR), vol. 3, no. 2, pp. 1-8, 2019.
31. Allouh, Majd N, et al., "Heart attack analysis & Prediction: A Neural Network Approach with Feature Analysis.", International Journal of Academic Information Systems Research (IJAISR), vol. 7, no. 9, pp. 47-54, 2023.
32. Al-Madhoun, Mohammed Ashraf, et al., "Neural Network-Based Water Quality Prediction", International Journal of Academic Information Systems Research (IJAISR), vol. 7, no. 9, pp. 25-31, 2023.
33. Al-Masawabe, Marah M, et al., "Papaya maturity Classification Using Deep Convolutional Neural Networks", International Journal of Engineering and Information Systems (IJEAIS), vol. 5, no. 12, pp. 60-67, 2021.
34. Al-Massri, Remah, et al., "Classification Prediction of SBRCTs Cancers Using Artificial Neural Network", International Journal of Academic Engineering Research (IJAER), vol. 2, no. 11, pp. 1-7, 2018.
35. Al-Mobayed, Awni Ahmed, et al., "Artificial Neural Network for Predicting Car Performance Using JNN", International Journal of Engineering and Information Systems (IJEAIS), vol. 4, no. 9, pp. 139-145, 2020.
36. Al-Mubayyed, Osama M, et al., "Predicting Overall Car Performance Using Artificial Neural Network", International Journal of Academic and Applied Research (IJAAR), vol. 3, no. 1, pp. 1-5, 2019.
37. Alqedra, Heba IA, et al., "Revolutionizing Lemon Quality Control: A Convolutional Neural Network Approach", International Journal of Academic Information Systems Research (IJAISR), vol. 9, no. 6, pp. 56-63, 2025.
38. Al-Rayes, Marwan RM, et al., "Smoke Detectors Using ANN", International Journal of Academic Engineering Research (IJAER), vol. 7, no. 10, pp. 1-9, 2023.
39. Al-Sharif, Ahmed Muhammad Haider, et al., "Predicting Heart Disease using Neural Networks", International Journal of Academic Information Systems Research (IJAISR), vol. 7, no. 9, pp. 40-46, 2023.
40. Al-Shawwa, Mohammed, et al., "Predicting Birth Weight Using Artificial Neural Network", International Journal of Academic Health and Medical Research (IJAHMR), vol. 3, no. 1, pp. 9-14, 2019.
41. Al-Shawwa, Mohammed, et al., "Predicting Effect of Oxygen Consumption of Thylakoid Membranes (Chloroplasts) from Spinach after Inhibition Using Artificial Neural Network", International Journal of Academic Engineering Research (IJAER), vol. 3, no. 2, pp. 15-20, 2019.
42. Al-Shawwa, Mohammed, et al., "Predicting Temperature and Humidity in the Surrounding Environment Using Artificial Neural Network", International Journal of Academic Pedagogical Research (IJAPR), vol. 2, no. 9, pp. 1-6, 2018.
43. Ashqar, Belal A M, et al., "Identifying Images of Invasive Hydrangea Using Pre-Trained Deep Convolutional Neural Networks", International Journal of Academic Engineering Research (IJAER), vol. 3, no. 3, pp. 28-36, 2019.
44. Attia, Maher Wissam, et al., "Predicting Fire Alarms in Smoke Detection using Neural Networks", International Journal of Academic Information Systems Research (IJAISR), vol. 7, no. 10, pp. 26-33, 2023.
45. Baraka, Raghad Fattouh, et al., "Predicting Books' Rating Using Just Neural Network", International Journal of Engineering and Information Systems (IJEAIS), vol. 7, no. 9, pp. 14-19, 2023.
46. Barhoom, Alaa M, et al., "Predicting Titanic Survivors using Artificial Neural Network", International Journal of Academic Engineering Research (IJAER), vol. 3, no. 9, pp. 8-12, 2019.
47. Dalffa, Mohaned Abu, et al., "Tic-Tac-Toe Learning Using Artificial Neural Networks", International Journal of Engineering and Information Systems (IJEAIS), vol. 3, no. 2, pp. 9-19, 2019.
48. Dawood, Kamel Jamal, et al., "Artificial Neural Network for Mushroom Prediction", International Journal of Academic Information Systems Research (IJAISR), vol. 4, no. 10, pp. 9-17, 2020.
49. Dawoud, Alaa Mohammed, et al., "Predicting Life Expectancy in Diverse Countries Using Neural Networks: Insights and Implications", International Journal of Academic Engineering Research (IJAER), vol. 7, no. 9, pp. 46-54, 2023.
50. Dheir, Ibtesam M, et al., "Classifying Nuts Types Using Convolutional Neural Network", International Journal of Academic Information Systems Research (IJAISR), vol. 3, no. 12, pp. 12-18, 2020.
51. El_Jerjawi, Nesreen Samer, et al., "Diabetes Prediction Using Artificial Neural Network", International Journal of Advanced Science and Technology, vol. 121, pp. 55-64, 2018.
52. El-Khatib, Mohmmad Jamal, et al., "Glass Classification Using Artificial Neural Network", International Journal of Academic Pedagogical Research (IJAPR), vol. 3, no. 2, pp. 25-31, 2019.
53. El-Mahelawi, Jamal Khamis, et al., "Tumor Classification Using Artificial Neural Networks", International Journal of Academic Engineering Research (IJAER), vol. 4, no. 11, pp. 8-15, 2020.
54. Elmahmoum, Abedeleilah SA, et al., "Image-Based Classification of Date Types Using Convolutional Neural Networks", International Journal of Academic Information Systems Research (IJAISR), vol. 9, no. 1, pp. 10-16, 2025.
55. Elzamly, Abdelrafe, et al., "Predicting Critical Cloud Computing Security Issues using Artificial Neural Network (ANNs) Algorithms in Banking Organizations", International Journal of Information Technology and Electrical Engineering, vol. 6, no. 2, p. 40-45, 2017.
56. Hadi, Ahmed Munther Abdel, et al., "Forecasting Stock Prices using Artificial Neural Network", International Journal of Engineering and Information Systems (IJEAIS), vol. 7, no. 10, pp. 42-50, 2023.
57. Harara, Mahmoud, et al., "Unlocking Literary Insights: Predicting Book Ratings with Neural Networks", International Journal of Academic Information Systems Research (IJAISR), vol. 7, no. 10, pp. 22-27, 2023.
58. Harz, Hussam Hatem, et al., "Artificial Neural Network for Predicting Diabetes Using JNN", International Journal of Academic Engineering Research (IJAER), vol. 4, no. 10, pp. 14-22, 2020.
59. Hasan, Walaa, et al., "Artificial Neural Network for Predicting COVID 19 Using JNN", International Journal of Academic Engineering Research (IJAER), vol. 7, no. 10, pp. 41-47, 2023.
60. Hassanein, Raghad Adnan Abu, et al., "Artificial Neural Network for Predicting Workplace Absenteeism", International Journal of Academic Engineering Research (IJAER), vol. 4, no. 9, pp. 62-67, 2020.
61. Heriz, Hazem Hatem, et al., "English Alphabet Prediction Using Artificial Neural Networks", International Journal of Academic Pedagogical Research (IJAPR), vol. 2, no. 11, pp. 8-14, 2018.
62. Jamala, Mohammed N, et al., "Predicting MPG for Automobile Using Artificial Neural Network Analysis", International Journal of Academic Information Systems Research (IJAISR), vol. 2, no. 10, pp. 5-21, 2018.
63. Jarghon, Amira, et al., "Predicting Kidney Stone Presence from Urine Analysis: A Neural Network Approach using JNN", International Journal of Academic Information Systems Research (IJAISR), vol. 7, no. 9, pp. 32-39, 2023.
64. Kashf, Dalia Wajeeh Abu, et al., "Predicting DNA Lung Cancer using Artificial Neural Network", International Journal of Academic Pedagogical Research (IJAPR), vol. 2, no. 10, pp. 6-13, 2018.
65. Khalil Ahmed, J, et al., "Energy Efficiency Prediction using Artificial Neural Network", International Journal of Academic Pedagogical Research (IJAPR) _, vol. 3, no. 9, pp. 1-7, 2019.
66. Kweik, Ola Mohammed Abu, et al., "Artificial Neural Network for Lung Cancer Detection", International Journal of Academic Engineering Research (IJAER), vol. 4, no. 11, pp. 1-7, 2020.
67. Maghari, Alaa Mazen, et al., "Books' Rating Prediction Using Just Neural Network", International Journal of Engineering and Information Systems (IJEAIS), vol. 4, no. 10, pp. 17-22, 2020.
68. Malekpourheydari, SALIMEH, et al., "Wavelet transform and neural network model for streamflow forecasting", J. Theor. Appl. Inf. Technol, vol. 100, 2022.
69. Marouf, Ahmad, et al., "Predicting Antibiotic Susceptibility Using Artificial Neural Network", International Journal of Academic Pedagogical Research (IJAPR), vol. 2, no. 10, pp. 1-5, 2018.
70. Mattar, Mohammad Ayman, et al., "Spotify Status Dataset", International Journal of Engineering and Information Systems (IJEAIS), vol. 7, no. 10, pp. 14-21, 2023.
71. Metwally, Najla'Fathi, et al., "Diagnosis of Hepatitis Virus Using Artificial Neural Network", International Journal of Academic Pedagogical Research (IJAPR), vol. 2, no. 11, pp. 1-7, 2018.
72. Mohammed, Ghaida Riyad, et al., "Predicting the Age of Abalone from Physical Measurements Using Artificial Neural Network", International Journal of Academic and Applied Research (IJAAR), vol. 4, no. 11, pp. 7-12, 2020.
73. Musleh, Musleh M, et al., "Predicting Liver Patients using Artificial Neural Network", International Journal of Academic Information Systems Research (IJAISR), vol. 3, no. 10, pp. 1-11, 2019.
74. Nasser, Ibrahim M, et al., "A Proposed Artificial Neural Network for Predicting Movies Rates Category", International Journal of Academic Engineering Research (IJAER), vol. 3, no. 2, pp. 21-25, 2019.
75. Nasser, Ibrahim M, et al., "Artificial Neural Network for Diagnose Autism Spectrum Disorder", International Journal of Academic Information Systems Research (IJAISR), vol. 3, no. 2, pp. 27-32, 2019.
76. Nasser, Ibrahim M, et al., "Artificial Neural Network for Predicting Animals Category", International Journal of Academic and Applied Research (IJAAR), vol. 3, no. 2, pp. 18-24, 2019.
77. Nasser, Ibrahim M, et al., "Developing Artificial Neural Network for Predicting Mobile Phone Price Range", International Journal of Academic Information Systems Research (IJAISR), vol. 3, no. 2, pp. 1-6, 2019.
78. Nasser, Ibrahim M, et al., "Lung Cancer Detection Using Artificial Neural Network", International Journal of Engineering and Information Systems (IJEAIS), vol. 3, no. 3, pp. 17-23, 2019.
79. Nasser, Ibrahim M, et al., "Predicting Books' Overall Rating Using Artificial Neural Network", International Journal of Academic Engineering Research (IJAER), vol. 3, no. 8, pp. 11-17, 2019.
80. Nasser, Ibrahim M, et al., "Predicting Tumor Category Using Artificial Neural Networks", International Journal of Academic Health and Medical Research (IJAHMR), vol. 3, no. 2, pp. 1-7, 2019.
81. Nasser, Mohammed S Abu, et al., "Leveraging Artificial Neural Networks for Cancer Prediction: A Synthetic Dataset Approach", International Journal of Academic Engineering Research (IJAER), vol. 7, no. 11, pp. 43-51, 2023.
82. Qamar, Sulafa Yhaya Abu, et al., "Predicting the Number of Calories in a Dish Using Just Neural Network", International Journal of Academic Information Systems Research (IJAISR), vol. 7, no. 10, pp. 1-9, 2023.
83. Qarmout, Hussein Khaled, et al., "Alzheimer: A Neural Network Approach with Feature Analysis.", International Journal of Academic Information Systems Research (IJAISR), vol. 7, no. 10, pp. 10-18, 2023.
84. Qwaider, Sabreen R, et al., "Artificial Neural Network Prediction of the Academic Warning of Students in the Faculty of Engineering and Information Technology in Al-Azhar University-Gaza", International Journal of Academic Information Systems Research (IJAISR), vol. 4, no. 8, pp. 16-22, 2020.
85. Sabah, Ahmed S, et al., "Pistachio Variety Classification using Convolutional Neural Networks", International Journal of Academic Information Systems Research (IJAISR), vol. 8, no. 4, pp. 113-119, 2024.
86. Sadek, Ramzi M, et al., "Parkinson's Disease Prediction Using Artificial Neural Network", International Journal of Academic Health and Medical Research (IJAHMR), vol. 3, no. 1, pp. 1-8, 2019.
87. Safiah, Saja Kh Abu, et al., "Climate Change temperature Prediction Using Just Neural Network", International Journal of Academic Engineering Research (IJAER), vol. 7, no. 9, pp. 35-45, 2023.
88. Salah, Mohammed, et al., "Predicting Medical Expenses Using Artificial Neural Network", International Journal of Engineering and Information Systems (IJEAIS), vol. 2, no. 20, pp. 11-17, 2018.
89. Samhan, Lamis F, et al., "Classification of Alzheimer's Disease Using Convolutional Neural Networks", International Journal of Academic Information Systems Research (IJAISR), vol. 6, no. 3, pp. 18-23, 2022.
90. Sultan, Alaa Yousef Abu, et al., "Neural Style Transfer Using Convolutional Neural Networks: An Experimental Study", International Journal of Academic Information Systems Research (IJAISR), vol. 10, no. 2, pp. 50-57, 2026.
91. Sultan, Anas Bachir Abu, et al., "Predictive Modeling of Breast Cancer Diagnosis Using Neural Networks: A Kaggle Dataset Analysis", International Journal of Academic Engineering Research (IJAER), vol. 7, no. 9, pp. 1-9, 2023.
92. Younis, Ibrahim, et al., "Prediction Heart Attack using Artificial Neural Networks (ANN)", International Journal of Engineering and Information Systems (IJEAIS), vol. 7, no. 10, pp. 36-41, 2023.
93. Zaiter, Ahmed Salama Abu, et al., "Web page phishing detection Using Neural Network", International Journal of Engineering and Information Systems (IJEAIS), vol. 7, no. 9, pp. 1-13, 2023.