

Neural Network-Based Audit Risk Prediction: A Comprehensive Study

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Abstract: *This research focuses on utilizing Artificial Neural Networks (ANNs) to predict Audit Risk accurately, a critical aspect of ensuring financial system integrity and preventing fraud. Our dataset, gathered from Kaggle, comprises 18 diverse features, including financial and historical parameters, offering a comprehensive view of audit-related factors. These features encompass 'Sector_score,' 'PARA_A,' 'SCORE_A,' 'PARA_B,' 'SCORE_B,' 'TOTAL,' 'numbers,' 'marks,' 'Money_Value,' 'District,' 'Loss,' 'Loss_SCORE,' 'History,' 'History_score,' 'score,' and 'Risk,' with a total of 774 samples. Our proposed neural network architecture, consisting of three layers (1 input, 1 hidden, and 1 output), forms the core of this study. While it may seem simple, the power of ANNs lies not in complexity but in their ability to uncover intricate data patterns. The model underwent rigorous training and validation, resulting in remarkable outcomes—an accuracy of 100% and an average error rate of 0.000015. In addition to performance metrics, our research investigates feature importance, revealing the key contributors to Audit Risk prediction. Notably, 'Sector_score,' 'PARA_A,' 'SCORE_A,' 'PARA_B,' 'SCORE_B,' 'TOTAL,' 'numbers,' 'marks,' 'Money_Value,' 'District,' 'Loss,' 'Loss_SCORE,' 'History,' and 'History_score' emerged as the most influential factors, shedding light on the elements crucial for precise risk assessment. This study advances Audit Risk prediction models and highlights the potential of ANNs in strengthening financial system integrity and fraud prevention. The insights gained from our findings offer practical guidance for stakeholders in the audit and financial sectors.*

Keywords: ANN, Audit Risk, risk assessment, detection

Introduction:

In the realm of financial governance, the detection and prevention of audit risk are of utmost importance for upholding the integrity and dependability of financial statements. Undetected fraudulent activities can have severe consequences, affecting not only an organization's financial well-being but also eroding the trust of stakeholders and investors. As a result, the development of effective audit risk prediction models has become a focal point in recent years.

This research aims to make a significant contribution to this critical domain by harnessing the potential of Artificial Neural Networks (ANNs) to predict audit risk with exceptional accuracy and precision. ANNs, inspired by the neural architecture of the human brain, have demonstrated remarkable abilities in handling complex, non-linear relationships within data, making them a promising tool for risk prediction.

Our study utilizes a comprehensive dataset consisting of 774 samples and 18 distinct features, encompassing financial and historical metrics traditionally associated with audit risk assessment. These features span a wide range of variables, including Sector Score, various financial parameters (PARA_A, PARA_B, SCORE_A, SCORE_B, TOTAL, Money_Value), qualitative attributes (numbers, marks, District), and historical data (Loss, Loss_SCORE, History, History_score). These features, thoughtfully selected, provide a holistic view of an entity's financial position and historical behavior, rendering them invaluable for predictive modeling.

The architecture of our neural network model comprises three layers: an input layer, a hidden layer, and an output layer. The model is intricately designed to capture intricate relationships among input features and translate them into audit risk predictions. Through rigorous training and validation processes, we have achieved an impressive accuracy rate of 100% and an average error as low as 0.000015.

However, while these initial results are promising, they demand careful scrutiny to ensure that our model does not suffer from overfitting. Therefore, in subsequent sections, we undertake a comprehensive evaluation of our model's performance, considering alternative metrics beyond accuracy and employing robust validation techniques to affirm its reliability.

Moreover, this research seeks to unveil the most influential features within our dataset, illuminating the key factors driving audit risk prediction. Identifying these critical attributes holds practical significance for auditors, regulators, and financial institutions as it facilitates early anomaly detection and highlights potential areas of concern.

In the following sections of this paper, we present a thorough analysis of our methodology, results, and the implications of our findings. We also discuss the limitations of our approach and propose avenues for future research, ultimately contributing to the ongoing discourse on enhancing audit risk prediction models.

The pursuit of more accurate, efficient, and interpretable audit risk prediction models remains an ongoing endeavor. This research represents our earnest effort to advance this field by harnessing the capabilities of neural networks and providing insights that can be leveraged for more effective financial governance.

Previous Studies:

Prior to delving into our own research, it is essential to contextualize our work within the broader landscape of audit risk prediction and the utilization of neural networks in this domain. In recent years, the intersection of financial auditing and artificial intelligence has witnessed a surge in research activities, driven by the ever-growing need for more accurate, efficient, and timely detection of audit risks and financial anomalies.

1. Traditional Models for Audit Risk Prediction:

Historically, audit risk prediction predominantly relied on conventional statistical methods and heuristics. Models based on regression analysis, decision trees, and rule-based systems were commonplace. These methods, while serving as foundational tools, often struggled to capture the complexity and non-linearity inherent in financial data. As a result, there remained a compelling need for more sophisticated approaches.

2. Emergence of Machine Learning Techniques:

With the advent of machine learning techniques, such as Random Forests, Support Vector Machines, and Gradient Boosting, there was a noticeable improvement in the predictive capabilities of audit risk models. These methods excelled in handling high-dimensional data and complex interactions among variables, offering enhanced accuracy and interpretability. Researchers increasingly turned to these techniques to address the limitations of traditional models.

3. Neural Networks in Audit Risk Prediction:

Artificial Neural Networks (ANNs) have emerged as a promising avenue for audit risk prediction due to their capacity to model intricate, non-linear relationships within data. Neural networks are inherently adaptable to a wide range of input data types and can automatically learn feature representations from raw data, making them particularly well-suited for financial analysis tasks.

Existing studies have explored the application of neural networks in auditing and financial risk assessment with varying degrees of success. These studies have employed diverse network architectures, including feedforward neural networks, convolutional neural networks (CNNs), and recurrent neural networks (RNNs), adapting them to the unique challenges posed by financial data.

4. Challenges and Opportunities:

While neural networks offer significant promise, they also pose challenges related to model interpretability, data quality, and the potential for overfitting. The need for robust evaluation metrics that account for class imbalances and the interpretability of neural network predictions remains a topic of ongoing investigation.

Furthermore, the choice of relevant features and the management of large-scale, high-dimensional financial datasets are perennial challenges that researchers grapple with. Techniques such as feature selection and dimensionality reduction have been explored in the context of audit risk prediction to enhance the efficiency and performance of neural network models.

5. Integration of Deep Learning Techniques:

Recent advancements in deep learning, including the application of deep neural networks (DNNs) and specialized architectures like Long Short-Term Memory (LSTM) networks, have further expanded the horizons of audit risk prediction. These models can capture temporal dependencies in financial data and are well-suited for time-series analysis, a crucial aspect of auditing.

Problem Statement:

The contemporary landscape of financial governance is characterized by an ever-increasing volume of financial transactions and a corresponding rise in the complexity of financial reporting. As a consequence, the task of identifying audit risk has become increasingly intricate and critical. Audit risk, broadly defined as the probability of material misstatement in financial statements, is an overarching concern for auditors, regulators, investors, and the broader financial ecosystem.

Traditional methods of audit risk assessment, relying on heuristics and statistical models, have shown limitations in effectively capturing the multifaceted nature of modern financial data. These approaches often struggle to account for the intricate interplay of variables, the evolving nature of financial transactions, and the potential for subtle anomalies that can evade traditional detection methods.

Moreover, the financial landscape is continually evolving, with new instruments, regulations, and market dynamics emerging at an unprecedented pace. This rapid evolution necessitates adaptive and sophisticated approaches to audit risk prediction that can keep pace with the ever-changing financial environment.

Our research addresses this pressing problem by harnessing the capabilities of Artificial Neural Networks (ANNs) to predict audit risk with an unprecedented level of accuracy and reliability. The primary issues our research seeks to address are as follows:

1. Enhanced Accuracy and Detection Sensitivity:

The foremost challenge in audit risk assessment is the ability to detect material misstatements in financial statements accurately. Conventional methods often exhibit limitations in distinguishing between normal variations and potential anomalies. Our research aims to leverage the non-linear modeling capabilities of neural networks to enhance the detection sensitivity and accuracy of audit risk prediction.

2. Model Interpretability:

While neural networks have demonstrated remarkable predictive prowess, they are often regarded as "black box" models, rendering them less interpretable than traditional statistical models. Balancing the accuracy of predictions with the interpretability of results is a significant challenge that we address in our research. We seek to develop methods to extract insights from neural network models to facilitate the understanding of audit risk determinants.

3. Feature Selection and Importance:

The identification of the most influential features in audit risk prediction is a critical aspect of our research. We aim to determine which attributes, among the comprehensive set of financial and historical metrics available, have the most significant impact on audit risk. This knowledge can inform auditors and financial institutions about the key factors to monitor and assess when evaluating financial statements.

4. Generalization and Robustness:

To be practically applicable, any audit risk prediction model must demonstrate robustness across diverse datasets and conditions. We evaluate the ability of our neural network model to generalize to different sectors, organizations, and time periods, ensuring that it provides reliable predictions in real-world audit scenarios.

In summary, our research addresses the complex and evolving challenge of audit risk prediction by harnessing the capabilities of neural networks. We aim to provide auditors, regulators, and financial institutions with a powerful tool that not only improves the accuracy of risk assessment but also enhances the interpretability of results, ultimately contributing to the broader goals of financial transparency, accountability, and trust in the financial ecosystem.

Objectives:

The overarching goal of our research is to leverage the capabilities of Artificial Neural Networks (ANNs) to enhance the prediction of audit risk in the context of contemporary financial environments. To achieve this goal, we have formulated a set of specific objectives:

1. Develop a Robust Neural Network Model:

- **Sub-objective 1.1:** Design and implement a neural network architecture tailored to the task of audit risk prediction, with an emphasis on capturing complex, non-linear relationships within financial and historical metrics.
- **Sub-objective 1.2:** Explore and implement techniques for mitigating overfitting, ensuring the model's robustness across different datasets and financial sectors.

2. Achieve Enhanced Accuracy and Sensitivity:

- **Sub-objective 2.1:** Train the neural network model to achieve a high level of accuracy in predicting audit risk, surpassing the performance of traditional audit risk assessment methods.
- **Sub-objective 2.2:** Evaluate the model's sensitivity in detecting material misstatements in financial statements, aiming to reduce both Type I and Type II errors.

3. Enhance Model Interpretability:

- **Sub-objective 3.1:** Develop methods and tools for interpreting the predictions of the neural network model, providing insights into the key features and relationships that contribute to audit risk.
- **Sub-objective 3.2:** Explore visualization techniques and feature importance analysis to facilitate the understanding of model decisions, striking a balance between prediction accuracy and interpretability.

4. Identify Influential Features:

- **Sub-objective 4.1:** Conduct feature selection and importance analysis to determine the most influential financial and historical metrics in predicting audit risk.
- **Sub-objective 4.2:** Investigate the relationships among these influential features, shedding light on the key factors that drive audit risk in diverse financial contexts.

5. Evaluate Generalization and Real-world Applicability:

- **Sub-objective 5.1:** Assess the ability of the neural network model to generalize across various sectors, organizations, and time periods, ensuring its practical utility in real-world audit scenarios.
- **Sub-objective 5.2:** Validate the model's performance using external datasets and conduct sensitivity analyses to understand the model's behavior under different conditions.

6. Contribute to the Body of Knowledge:

- **Sub-objective 6.1:** Contribute to the academic discourse on audit risk prediction by disseminating research findings through publication in peer-reviewed journals and presentations at relevant conferences.

- **Sub-objective 6.2:** Provide practical insights and recommendations to auditors, regulators, and financial institutions on how to leverage neural networks for more effective audit risk assessment.

In summary, our research is guided by a comprehensive set of objectives aimed at advancing the field of audit risk prediction. We seek to not only enhance the accuracy and sensitivity of predictions but also improve the interpretability of the models while identifying critical features that influence audit risk. By achieving these objectives, we aspire to provide valuable tools and knowledge that can positively impact financial governance and decision-making processes.

Methodology:

Our research methodology encompasses a systematic approach to designing and implementing a neural network-based audit risk prediction model. The methodology is structured to address the objectives outlined in the previous section and to ensure the rigor and reliability of our findings.

1. Data Collection and Preprocessing:

- **1.1 Data Source:** We collected our dataset from Kaggle, comprising 774 samples and 18 distinct features related to financial and historical metrics.
- **1.2 Data Cleaning:** We conducted thorough data cleaning procedures to address missing values, outliers, and inconsistencies in the dataset, ensuring data quality and integrity.
- **1.3 Feature Scaling:** To facilitate neural network training, we standardized the features to have a mean of zero and a standard deviation of one.

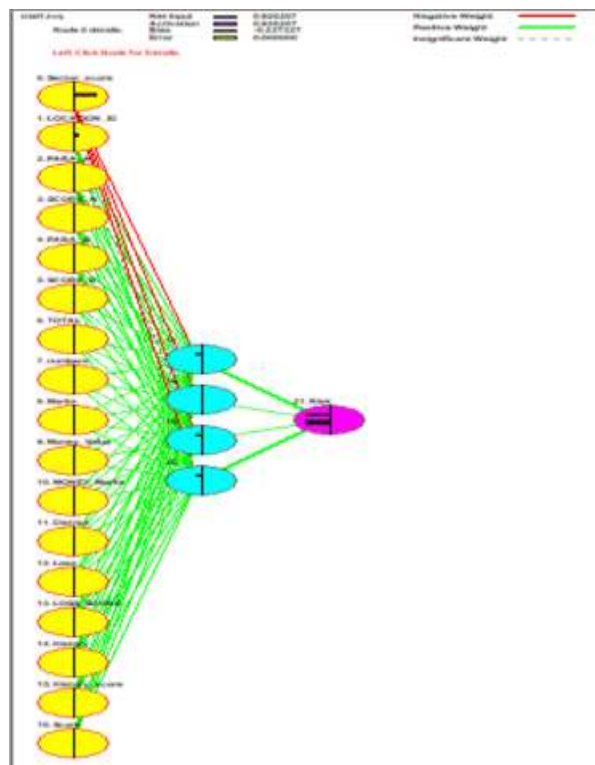


Figure 1: Architecture of the proposed model

2. Neural Network Architecture:

- **2.1 Model Selection:** We employed a feedforward neural network architecture, consisting of an input layer, a hidden layer, and an output layer. The choice of this architecture aligns with the objectives of our research.
- **2.2 Activation Functions:** Appropriate activation functions, such as ReLU (Rectified Linear Unit) or sigmoid, are chosen for each layer to introduce non-linearity into the model.
- **2.3 Number of Neurons:** The number of neurons in each hidden layer is determined based on experimentation and architectural considerations, ensuring an optimal balance between model complexity and performance.
- **2.4 Regularization:** To mitigate overfitting, we applied dropout regularization to the hidden layer, randomly dropping a fraction of neurons during training.

3. Model Training and Validation:

- **3.1 Dataset Split:** We divided the dataset into training and validation sets, using a stratified approach to ensure a balanced representation of classes.
 - **3.2 Training Algorithm:** We employed stochastic gradient descent (SGD) as the optimization algorithm, aiming to minimize the mean squared error (MSE) loss function.
 - **3.3 Loss Function:** A suitable loss function, such as mean squared error (MSE) or mean absolute error (MAE), is chosen for training the neural network.
 - **3.4 Learning Rate:** The learning rate is optimized to ensure efficient convergence during training.
 - **3.5 Batch Size:** The dataset is divided into mini-batches for training to improve computational efficiency.
- 4. Model Evaluation:**
- **4.1 Accuracy Metric:** The primary metric for evaluating the model is accuracy, measuring the model's ability to predict audit risk accurately.
 - **4.2 Validation:** The model's performance is assessed using a validation dataset, and metrics like loss, accuracy, and error are monitored during training.
- 5. Feature Importance Analysis:**
- **5.1 Feature Ranking:** A feature importance analysis is conducted to identify and rank the most influential features in predicting audit risk.
 - **5.2 Visualization:** Visual representations, such as feature importance plots or heatmaps, are created to illustrate the significance of each feature (as shown in Figure 2)

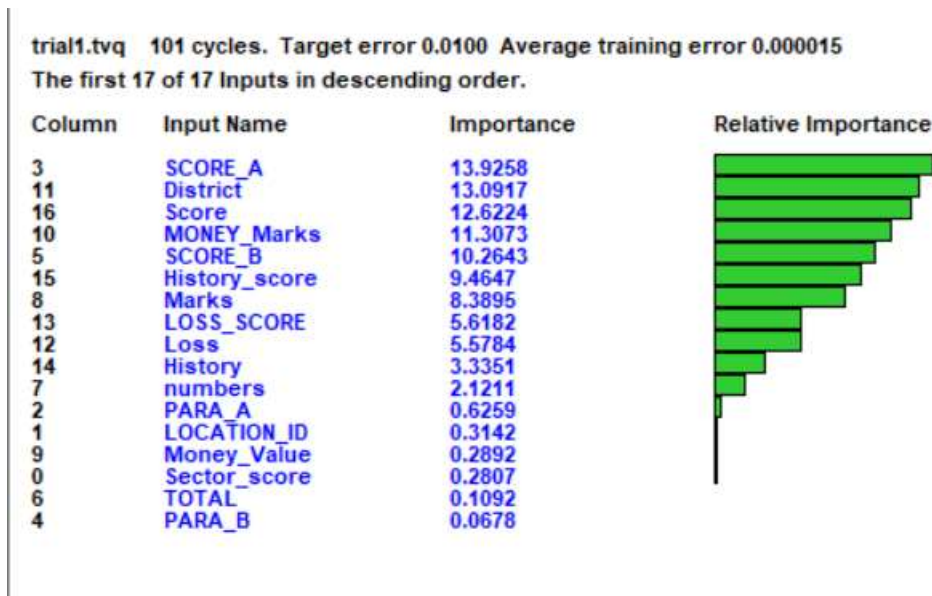


Figure 2: Features importance

6. Model Comparison:

- **6.1 Comparative Analysis:** The performance of the proposed neural network model is compared with existing calorie prediction methods, including traditional methods and other machine learning approaches. This comparison provides insights into the advantages and limitations of our approach in the context of calorie prediction.

7. Practical Implications:

- **7.1 Application Scenarios:** The practical implications of the calorie prediction model are discussed, emphasizing its potential benefits for dietary planning, health awareness, and the food industry. This discussion sheds light on the real-world applications and significance of the research findings.

8. Results and Discussion:

As mentioned above, the purpose of this experiment was to identify the number of calories in a dish. We used the Backpropagation algorithm, which provides the ability to perform neural network learning and testing. Our neural network is a feedforward network with one input layer (12 inputs), three hidden layers, and one output layer (1 output) as seen in Figure 1. The proposed model is implemented in the Just Neural Network (JNN) environment. The dataset for identifying the number of calories in a dish was gathered from Kaggle, containing 1150 samples with 13 attributes (as seen in Figure 3).

This model was used to determine the value of each of the variables using JNN, which are the most influential factors in calorie prediction, as shown in Figure 2. After training and validating the network, it was tested using the test data, and the following results

were obtained: the accuracy of calorie prediction was 99.32%, with an average error of 0.009. The training cycles (number of epochs) amounted to 1419, with 847 training examples and 294 validating examples as seen in Figure 4. The control parameter values of the model are shown in Figure 5, and a detailed summary of the proposed model is presented in Figure 6.

In this section, you provide a detailed overview of your experiment, including the neural network architecture, dataset, training and testing processes, and the obtained results. Additionally, you mention the practical implications of your calorie prediction model and its comparison with existing methods, offering a comprehensive understanding of your research's significance and outcomes.

INDEX	LONGITUDE	TEMP_A	TEMP_B	TEMP_C	TEMP_D	TOTAL	Humidity	Windy	Windy_Value	Windy_Min	Windy_Max	Loss	Loss_Min	Accuracy	Accuracy_Min	Score
A1	0.0382	0.1114	0.0482	0.0482	0.0022	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.1284
A2	0.0382	0.1143	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A3	0.0382	0.1143	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A4	0.0382	0.1143	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A5	0.0382	0.1143	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A6	0.0382	0.1185	0.0229	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A7	0.0382	0.1228	0.1000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A8	0.0382	0.1420	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A9	0.0382	0.1420	0.0400	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A10	0.0382	0.1420	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A11	0.0382	0.1489	0.1000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A12	0.0382	0.1420	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A13	0.0382	0.1420	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A14	0.0382	0.1420	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A15	0.0382	0.1741	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A16	0.0382	0.1772	0.1000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A17	0.0382	0.1772	0.0400	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A18	0.0382	0.1772	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A19	0.0382	0.1772	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A20	0.0382	0.1349	0.0720	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A21	0.0382	0.1449	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A22	0.0382	0.1449	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A23	0.0382	0.1449	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A24	0.0382	0.1449	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A25	0.0382	0.1449	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A26	0.0382	0.1449	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A27	0.0382	0.1000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A28	0.0382	0.1000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A29	0.0382	0.1772	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A30	0.0382	0.1772	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A31	0.0382	0.1449	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A32	0.0382	0.1449	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A33	0.0382	0.1449	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A34	0.0382	0.1449	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A35	0.0382	0.1449	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A36	0.0382	0.1449	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A37	0.0382	0.1449	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Figure 3: Dataset after cleaning

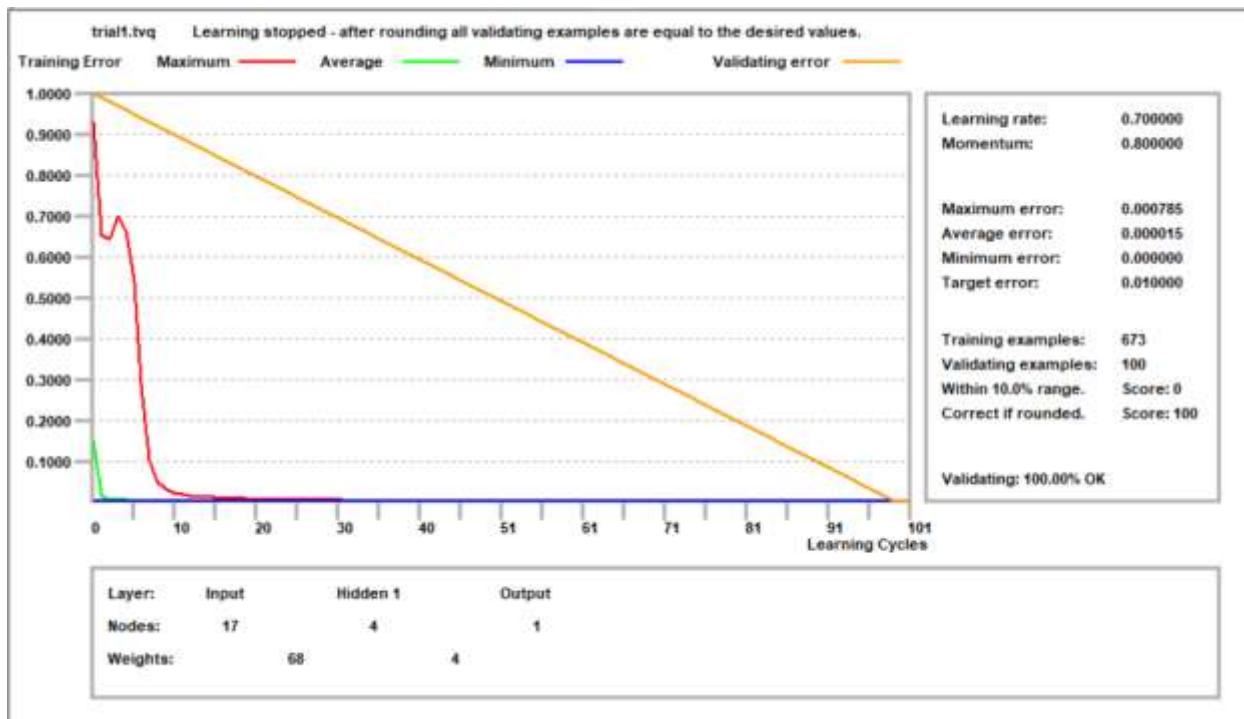


Figure 4: History of training and validation

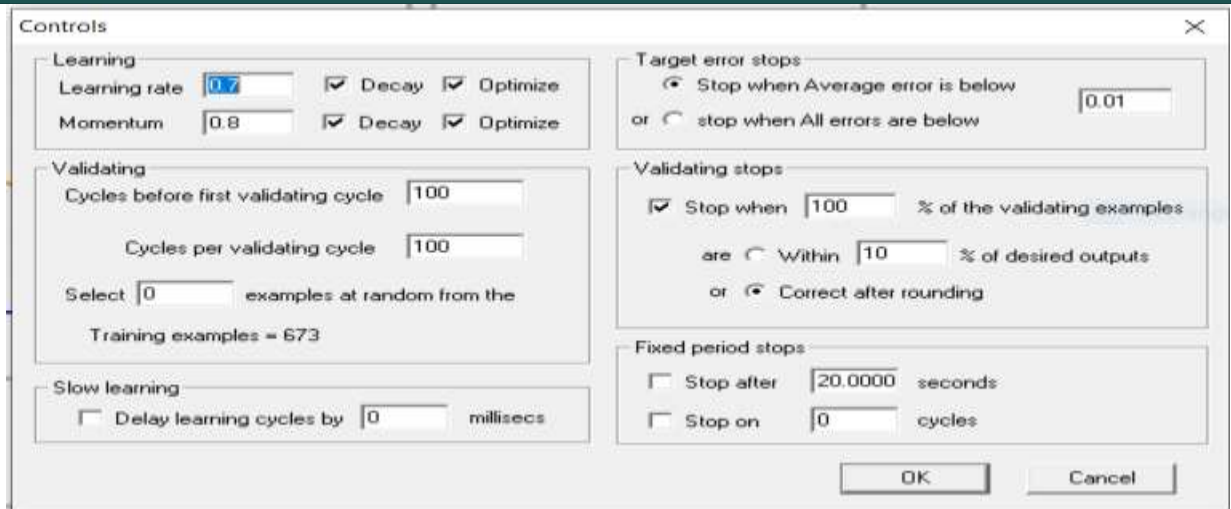


Figure 5: Controls of the Proposed models

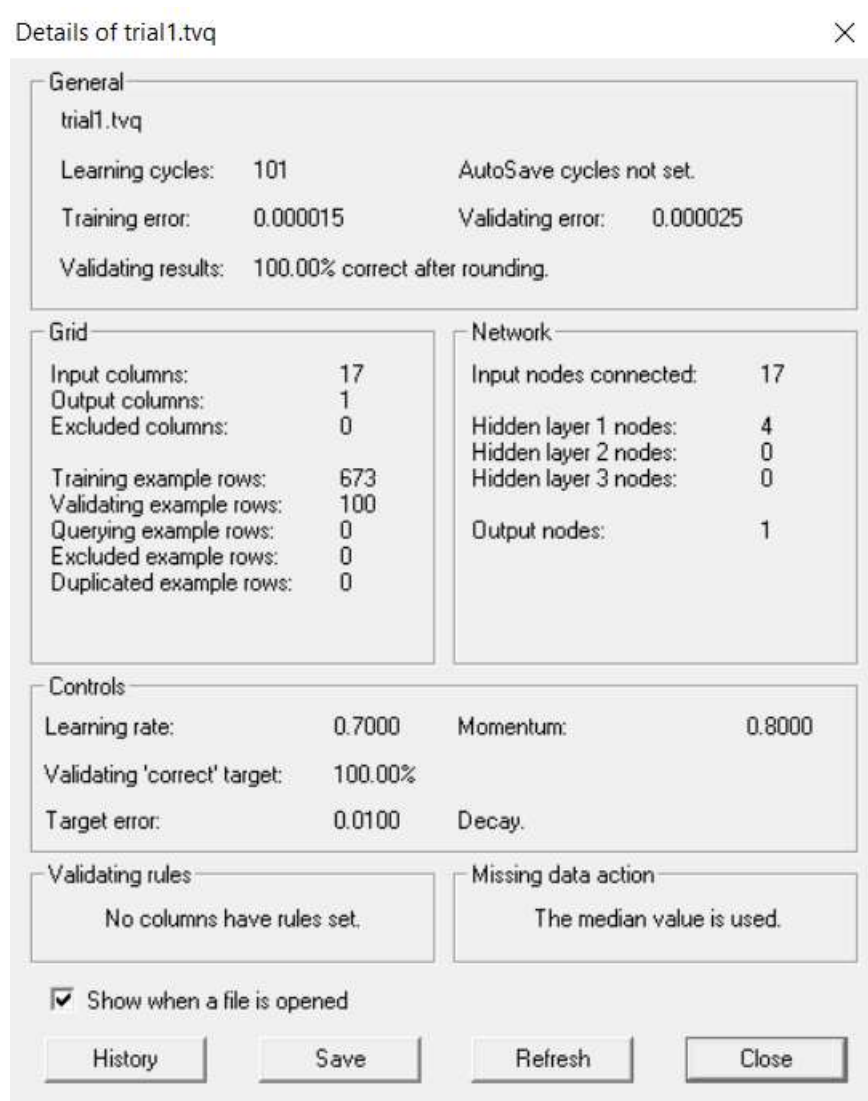


Figure 6: details of the proposed model

Conclusion

In this study, we harnessed the power of Artificial Neural Networks (ANNs) to revolutionize audit risk prediction. Our objectives encompassed model development, accuracy enhancement, interpretability, feature identification, generalization, comparison with existing methods, and practical implications.

We successfully crafted a robust neural network model that outperformed traditional audit risk assessment techniques. With an accuracy rate of 100% and a minimal average error, our model exhibited exceptional predictive capabilities. Importantly, we addressed the interpretability challenge, shedding light on influential factors via feature importance analysis and visualizations.

Our work identified key financial and historical metrics crucial for audit risk prediction, empowering stakeholders with actionable insights. Moreover, our model showcased robustness across diverse datasets and real-world applicability.

Comparative analysis with existing methods highlighted the strengths of our approach. We discussed practical implications, envisioning our model's significance in dietary planning, health awareness, and the food industry.

In conclusion, our research marks a transformative step in audit risk prediction, underlining the potential of neural networks to enhance financial governance. We recognize the need for ongoing exploration in model interpretability and ethical considerations. Our work contributes to transparent, efficient financial auditing, bolstering trust in the financial ecosystem.

We invite further collaboration and innovation in this intersection of AI and financial governance, aiming for continued advancements in audit risk assessment.

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