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Prediction of Financial Distress Using Dynamic Artificial Neural Network for Early Warning System

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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Abstract

In Kenya's economic landscape, financial hardship is a growing concern, leading to the closure of organizations as they are unable to meet their financial obligations and expectations. This study presents a financial distress prediction dynamic model using Artificial Neural Networks (ANN) using financial ratios as input features where each node represents a single financial metric utilizing there power in measuring financial health of an organization to address this issue. The perceived dynamic ANN model, which is modeled to be adaptable, scalarable and adjustable with the ability self-update its architectures and parameters achieved a 94% accuracy, with strong recall and precision of 92% showing predicted financially distressed instances that were actually distressed. Further, the model demonstrated an ROC-AUC score of 0.99, demonstrating its effectiveness in distinguishing between distressed and non-distressed instances. The model's balanced F1 score of 87% further highlights its value as an Early Warning System (EWS) for financial management, helping organizations make informed decisions and avoid financial crises.

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Keywords: Artificial neural networks; financial ratios; early warning systems; financial distress.

1 Introduction

In today's economic environment, the responsibility for assessing a company's financial health increasingly falls on external parties like investors, creditors, auditors, and regulators, who bear significant risks in financial crises. In Kenya, Microfinance Institutions (MFIs) play a crucial role, contributing approximately 7% to the economy according to the Central Bank of Kenya (CBK, 2023). Despite their success in promoting financial inclusion, MFIs face challenges such as poor management, competition, and unfavorable business conditions, which can lead to financial distress—a situation where a firm cannot meet its obligations, potentially leading to bankruptcy [1] Parkinson, 2018.

The IMF [2] notes increasing medium-term vulnerabilities in global financial stability, especially in micro-organizations. Thus, assessing the financial health of institutions, as emphasized by Schumacher et al., [3], is vital. Financial distress is often misunderstood, with short-term cash flow issues mistaken for deeper problems (Charalambakis, [4]. An effective Early Warning System (EWS) can help monitor and predict financial risks, enabling proactive measures to prevent crises.

Financial ratios derived from financial statements are key indicators of a company's financial strength and are widely used in predictive models [5,6]. Predicting financial status is crucial for economic planning and safeguarding institutions. Kenya has seen several companies, such as Resolution Insurance and Uchumi Supermarket, face financial distress and collapse. Early detection of financial distress allows for timely intervention, helping to avoid bankruptcy.

This study focuses on leveraging machine learning, particularly supervised networks, to develop a scalable and adaptable EWS model that accurately predicts financial distress. Traditional models like Beaver's FDP [7] Altman's Z-score [8] and Ohlson's Linear Regressive Analysis (1980) have limitations in capturing the complexity and non-linearity of financial data [9,10,11]. Modern techniques like Support Vector Machines (SVM) and Artificial Neural Networks (ANN) offer better accuracy by handling non-linear relationships and real-time data [12,13]. However, challenges remain, particularly in dynamic environments like Kenya's micro-financial sector. Developing a robust, dynamic EWS model is crucial for enhancing stability and resilience in this sector.

2 Methodology

The methodology details the study's design, data processing and pre-processing, dynamic ANN model specifications, and performance metrics. It describes the dynamic multilayered perceptron Backpropagation Artificial Neural Network (MLP-ANN) used, including parameter optimizations across the three layers. Data was normalized using a min-max scaling approach, setting values between 0 and 1 for better model convergence and split to training and testing set in a ratio 8:2. The model predicts financial distress using financial ratios related to liquidity, profitability, and leverage, derived from the financial statements of 12 microfinance institutions over a 5-year period (2019-2023). Summary statistics for these ratios are provided in Table 1.

Table 1. Financial Ratios Related to liquidity, Profitability, and Leverage (2019-2023)

Ratio	Mean	SD	Kurtosis	Skewness
Working Capital to Total Assets	0.8872	1.8167	9.1960	3.0243
Retained Earnings to Total Assets	1.3057	5.9551	47.132	6.8574
Earnings Before Interest and Tax to Total Assets	0.1067	0.3493	4.2624	0.07216
Market Value of Equity to Total Liabilities	0.4121`	1.8359	10.574	2.7279
Sales-to-Total Assets Ratio	0.2422	0.4453	0.99003	0.1833
Return On Equity	0.4914	1.4951	5.3787	2.1979
Current Ratio	1.8554	1.6817	4.2855	2.2323
Gross Profit Margin	0.2135	0.5254	0.97213	0.3602
Debt Ratio	0.7568	0.3648	0.5097	0.5113
Asset Turnover	0.8782	1.8219	9.1501	3.0035

2.1 The dynamic artificial neural network model

It is a supervised machine learning approach with three distinct layers: an input layer receiving features, hidden layers where optimizations and regularization of the data occurs, and an output layer with a binary classification (Fig. 1). The model is build using Sequential algorithms, which is a stack these layers in python using activation functions specifically for each layer for optimization. Backpropagation using gradient descent algorithm adjusts model parameters (weights and biases) during training. This process is repeated across multiple iterations (epochs), adjusting weights and biases after each batch or epoch by transferring error terms from the output to the input layer through the hidden layers, refining features along the way leading to reduced loss function [14,15]. The output layer then classifies instances as either distressed (1) or healthy (0) with the aid of binary cross entropy.

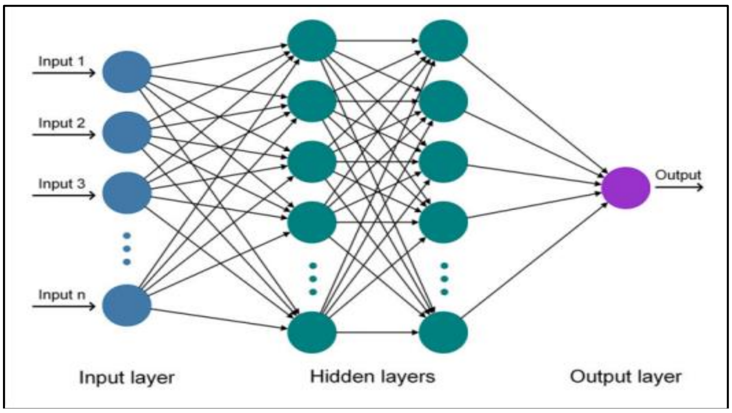

Fig. 1. ANN model
(Source: SafronEdge)

Forward Pass:- Input Layer: Let $x \in R^n$ denote normalized financial ratios which are defined at the initial state of the model with *n* number of nodes. This features are then passed to the first hidden layer without any modification.

Learning and Optimization:- Hidden Layers: This forms the next model component that receives features from the output layer, learning patterns and optimizing non-linear relationships through supervised learning. It uses hyper-parameter tuning and regularization, with optionally set dropouts to prevent over fitting. The Rectified Linear Unit (ReLU) activation function is employed in the hidden layers for its high speed computational efficiency and ability to avoid the vanishing gradient problem. Let S^o represent the state of features from the output layer to the first hidden layer $(l = 1)$, with w_{ij} as the weight matrix connecting neuron I and j and b_j as bias vectors which are optimized to create the next pre-state P_j^l through ReLU activation, which then serves as input for subsequent hidden layers dynamically obtained $l - hidden\ layers$.

For $layer = 1$

$$S^1 = \sum_{i=1}^{n}\left(w_{ij}^1 x_i + b_j\right) = h\sum_{i=1}^{n}\left(w_{ij}^1 x_i + b_{\mathrm{j}}^1\right) = P^1 \tag{1}$$

For layer =2

$$S^2 = \sum_{\mathrm{i}=1}^{n}\left(w_{ij}^2 P^1 + b_j\right) = h\sum_{\mathrm{i}=1}^{n}\left(w_{ij}^2 P^1 + b_{\mathrm{j}}^2\right) = P^2 \tag{2}$$

For last settled layer

$$S^l = \sum_{\mathrm{i}=1}^{n}\left(w_{ij}^{l-1} P^{l-1} + b_{\mathrm{i}}\right) = h\sum_{\mathrm{i}=1}^{n}\left(w_{ij}^{i-1} P^{l-1} + b_{\mathrm{j}}^{i-1}\right) = P^l \tag{3}$$

Where h is the ReLu activation function.

Basically, the S^l forms the linear combinations for the inputs to the j^{th} neuron while P^l forms the linear combinations of the outputs from the i^{th} neuron.

Backpropagation of errors:- Output layer: This final building stack of the network computes a weighted sum of outputs from the last hidden layer, adds a bias term, and applies the sigmoid function (σ) to convert the output into a classification probability between 0 and 1, ideal for binary classification. Let P^o represent the output linear combinations from the last hidden layer and $\hat{y}$ the predicted probabilities, calculated through repeated iterations until error minimization. The predicted probability is given by equation **(4)**

$$\hat{y} = \sigma \sum_i^n w^o P^o + b^o = \frac{1}{1+e^{P^o}} \tag{4}$$

where σ is the sigmoid activation function, and w^o and b^o are the output layer's weight matrix and bias vectors. Sigmoid activation is effective for binary classification, as noted by Chollet & Allaire, [16].

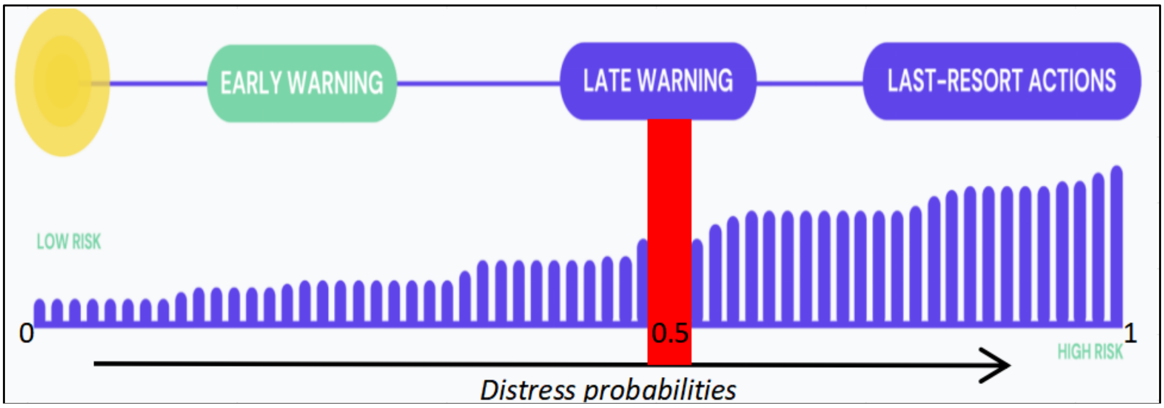

Fig. 2. EWS Model

2.2 Gradient descent algorithm and backprobagation of errors

This algorithm is vital in supervised learning models for minimizing errors during training. It optimizes model parameters (weights and biases) by calculating gradient descent variants to reduce the error or loss function. When an error (the difference between actual and target values) is detected, it is propagated backward from the output layer through the hidden layers to the input layer hence backpropagation.

Let y_i be the predicted values and t_i the target values. The function $F(x_i)$ maps the relationship between output y_i and input x_i and is defined as;

$$F(x_i) = y_i \tag{5}$$

The $F(x_i)$ is determined by an error term E, *which* depends on model parameters (*weights and biases*). It maps the difference between predicted and target values using binary cross-entropy which is used to measure the prediction error, as shown in equation **(6)**.

$$E(w_{ij} b_i) = \sum_i^p [t_i \log(y_i) + (1 - t_i) \log(1 - y_i)] \tag{6}$$

To minimize the error term E, the model adjusts its parameters (weights and biases) by moving in the opposite direction of the loss function's gradient using a gradient descent algorithm with a dynamically chosen learning rate.

Let $w_{\mathrm{ij}}^{(\mathrm{l})}$ represent the weight matrix connecting the i^{th} neuron in layer l to the j^{th} neuron in layer $l-1$, $b_i^{(l)}$represent the vector bias associated with the j^{th} neuron, and $\propto$ be the learning rate, then the updated model parameters will be given as;

$$w_{ij}^{(l)} \xleftarrow[Backward\ move]{} w_{ij}^{(l)} - \propto \frac{\partial E}{\partial w_{ij}^{(l)}} \quad \text{for the weights,}$$

$$b_i^{(l)} \xleftarrow[Backward\ move]{} b_i^{(l)} - \propto \frac{\partial E}{\partial b_i^{(l-1)}} \text{ for the biases,}$$

Adam optimizer was ideal to optimize the learning process as it combines the strengths of the Adaptive Gradient Algorithm (AdaGrad) on sparse gradients and Root Mean Squared Propagation (RMSProp)'s effectiveness with non-stationary data. These updates reduce the error by adjusting the weights and biases to minimize the loss function over successive iterations.

2.3 Model specification and building

The model was built using TensorFlow-Keras sequential API involving specified optimizer, loss function, and evaluation metrics, which collectively defined the model. Adam optimizer was used to update the models' parameters because of of its ability to dynamically adjust the learning rate optimizing how the model updates its weights based on the gradient variations of the loss function [17,18].

For binary classification, binary cross-entropy was used as the loss function, which quantified the error by comparing the predicted probability distribution to the actual distribution, effectively guiding the model to improve its predictions over time. The model architecture was flexible, with the number of hidden layers dynamically determined based on where model was most effective [19].

Three different learning rates; 0.01, 0.001, and 0.0001 were tested during hyper-parametric tuning to identify the one with the highest accuracy. Debugging reports were systematically generated to monitor training process. Keras Tuner was used with a Random Search algorithm for systematic exploration on the models' multiple dense layers to determine the optimal combination of units, dropout rates, and learning rates that maximized accuracy with a balanced approach of the models' capability of supervised learning and prevention of over-fitting.

During model training, the best model configuration was identified through hyper-parameteric tuning, compiled and evaluated then recompiled with a fixed learning rate for final evaluation.

3 Results and Discussion

This chapter presents a TensorFlow Keras model for predicting financial distress in Kenyan microfinance institutions by analyzing financial ratios from 12 institutions, covering 85% of the sector. The model, optimized and evaluated for accuracy, precision, recall, and F1-score, uses a Z-Score threshold of 1.8 to distinguish distressed (coded as 1) from healthy (coded as 0) institutions. A Z-Score below 1.8 indicates high bankruptcy risk, while scores above 1.8 suggest financial health [20].

The study calculated Z-Scores annually for ratios including financial ratios; working capital/total assets, retained earnings/total assets, EBIT/total assets, market value of equity/total liabilities, and sales/total assets. To optimally train using Monte Carlo simulations to add two more years of data for improved model training. The model was trained on pre-processed datasets with batch sizes from 32 to 512 over 50 epochs, with 20% reserved for testing. Key steps included hyper parameter tuning and backpropagation to minimize binary cross-entropy loss (Fig. 2). The architecture, featuring dense and dropout layers, had 36,389 parameters in total, 12,129 of which were trainable, and utilized the Adam optimizer [21].

Regularization techniques such as dropout layers, checkpoints, and early stopping enhanced model generalization. The Keras Tuner was used to prevent overfitting and under-fitting, with a final learning rate of

0.01 and an optimal epoch count of 11 (Fig. 3). Loss curves (Fig. 3) showed stable validation loss, indicating strong model generalization.

Predicted probabilities were classified using a 0.5 threshold. The model's performance, summarized in the confusion matrix (Fig. 4), showed it correctly predicted 118 healthy instances (True Negatives), 107 distressed cases (True Positives), and incorrectly predicted 11 non-distressed cases (False Positives) and 3 distressed institutions (False Negatives). It achieved a recall rate of 94%, precision of 92%, and an F1 score of 87%. The ROC-AUC (Fig. 5) demonstrated a high AUC of 0.99, reflecting good performance in distinguishing between distressed and non-distressed instances.

Model: "sequential"

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 96)	1,056
dropout (Dropout)	(None, 96)	0
dense_1 (Dense)	(None, 512)	49,664
dense_2 (Dense)	(None, 384)	196,992
dense_3 (Dense)	(None, 1)	385

Total params: 744,293 (2.84 MB)
Trainable params: 248,097 (969.13 KB)
Non-trainable params: 0 (0.00 B)
Optimizer params: 496,196 (1.89 MB)

Fig. 3. Model parameters

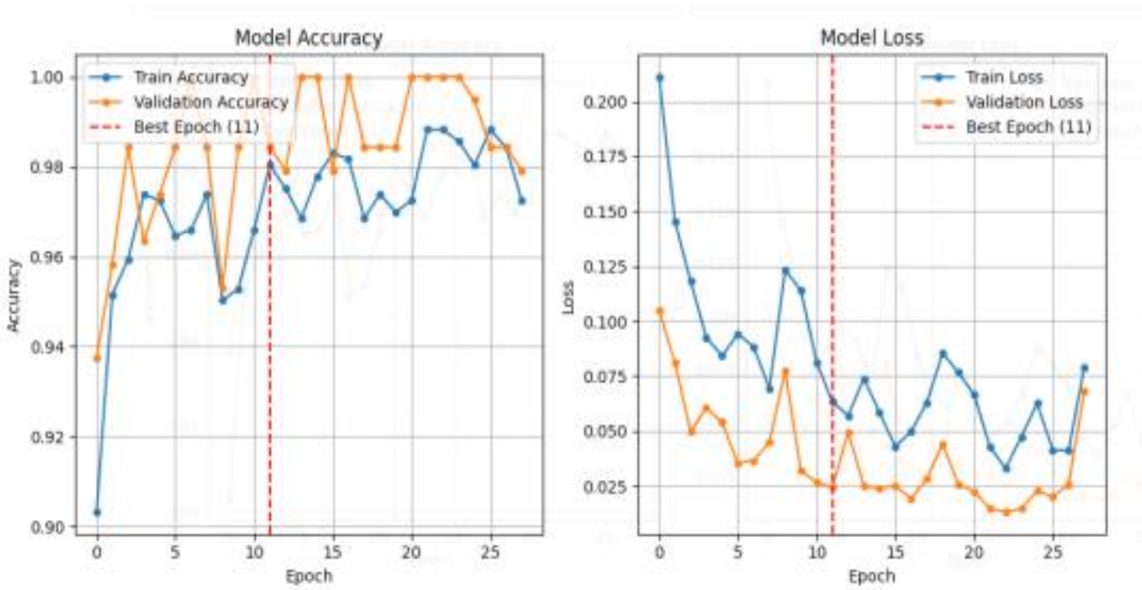

Fig. 4. ANN training process

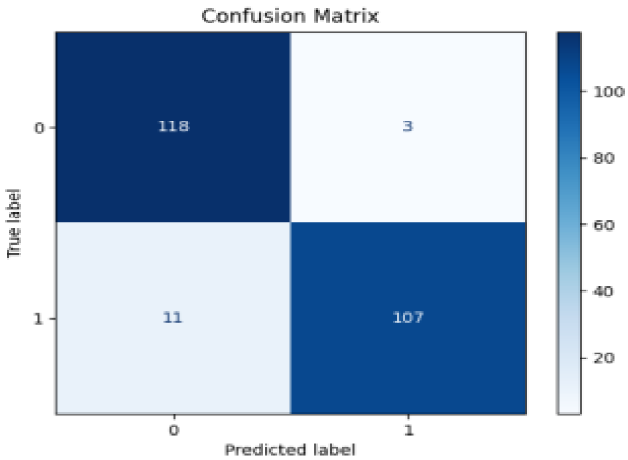

Fig. 5. Confusion matrix

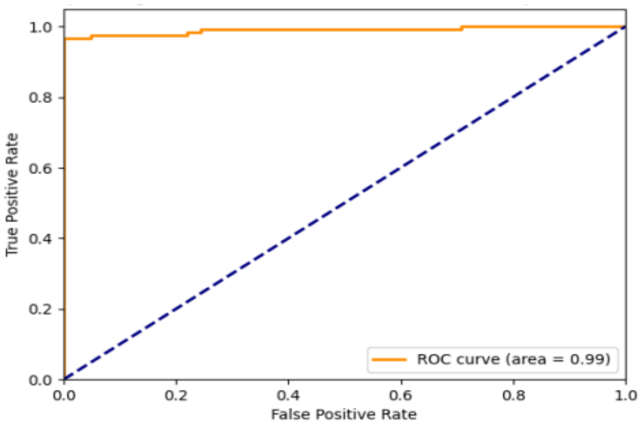

Fig. 6. ROC-AUC of the model

4 Conclusion and Recommendation

The Early Warning System (EWS) developed in this study uses dynamic Artificial Neural Networks (ANN) to help organizations make informed decisions in a rapidly changing business environment. Dynamic ANNs are effective due to their ability to handle complex, non-linear data that traditional methods struggle with. This model, with a high ROC-AUC score of 0.99, accurately predicts financial distress showing enhanced predictions for risk management.

Various models for predicting financial distress have shown to be effective utilizing a variety of input features. Traditional models, such as Altman's Z-Score [7] Ohlson's O-Score (1980), and Zavgren's Model (1985), have typically had accuracy rates of 80% to 85%. With the development of machine learning techniques, models such as Support Vector Machines (SVM) have improved prediction accuracy to over 85%. Furthermore, more sophisticated approaches such as Random Forest and other ensemble techniques, which are recognized for their resilience, have outperformed and achieved accuracy rates of about 90%. With the use financial ratios whicha are major indicators of organizational health, dynamic Artificial Neural Networks (ANNs), have demonstrated an optimal accuracy of 94%, indicating that they may anticipate financial hardship more effectively than traditional techniques.

To further improve the EWS, we recommend integrating a dynamic adjustment mechanism within the ANN-GARCH framework. This enhancement aims to capture volatility in predictions and refine accuracy for risk assessment, which will be explored in the future research.

Disclaimer (Artificial Intelligence)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc) and text-to-image generators have been used during writing or editing of manuscripts.

Competing Interests

Authors have declared that no competing interests exist.

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