ANN (Artificial Neural Network)

Niruthiha Selvnayagam
002413183
INFO6105 Fall 2024

Abstract

This report explores the implementation and performance of Artificial Neural Networks (ANNs) as part of a comparative study on supervised learning algorithms. Binary classification with minimal observations is a critical challenge in various domains where obtaining large amounts of training data is difficult, expensive, or ethically constrained. This study focuses on the application of machine learning techniques to two distinct areas: maternal health risk assessment,, a field where data limitations are particularly prevalent and impactful. and credit card customer churn prediction. Both fields present unique challenges in data availability and model performance.

1 Datasets

#	Dataset Name	Attributes	Instances	Data Type
1	Credit Card customers - Predict Churning customers	23	10,000	Numerical and Categorical
2	Maternal Health Risk Dataset	6	1,013	Numerical and Categorical

Table 1: Dataset Overview

Data set 1: `https://www.kaggle.com/datasets/sakshigoyal7/credit-card-customers`
Data set 2: `https://archive.ics.uci.edu/dataset/863/maternal+health+risk`

2 Why These Datasets Are Interesting

Both datasets address important problems in their respective fields (finance and healthcare), making them relevant for practical applications. Iexplore the application of Artificial Neural Networks (ANNs) to both tasks, acknowledging that while ANNs can capture complex patterns, they typically require larger datasets for optimal performance. My approach builds upon findings from previous research, such as the study by C. Li et al. (2014), which highlighted the common challenge of performance degradation in classification algorithms when working with limited data. Successful models built on these datasets could have tangible benefits, either in customer retention for the credit card company or in improving maternal healthcare outcomes.

3 Credit Card Customers - Predict Churning Customers

Predicting customer churn can significantly impact a company's revenue and customer retention strategies. With only 16.07% of customers churning, this dataset presents the common real-world challenge of class imbalance, requiring careful consideration in model selection and evaluation.

3.1 Data Preprocessing

A thorough cleaning process was performed, including checking for null values to ensure data integrity. Categorical variables were transformed into numerical format using Label Encoding, making them suitable for machine learning algorithms. Numerical features were standardized using StandardScaler to ensure equal contribution to the model and improve performance of scale-sensitive algorithms. A new feature, 'Credit_Utilization_Ratio', was created to capture customers' credit usage patterns, potentially enhancing the model's predictive power.

3.2 Artificial Neural Network (ANN) Structure

The ANN model architecture was designed to capture complex patterns in the customer churn data. It consists of an input layer shaped by the feature set, followed by three hidden layers with 64, 32, and 16 neurons respectively, each using ReLU activation. Dropout layers (rate 0.3) were added after each hidden layer for regularization. The output layer contains a single neuron with Sigmoid activation, suitable for binary classification.

3.2.1 Model Compilation and Training

The model was compiled using Binary Cross-Entropy loss, Adam optimizer, and Accuracy metric. It was trained for 50 epochs with a batch size of 32, balancing between model convergence and computational efficiency.

3.2.2 Model Performance

The ANN model achieved a test accuracy of 93% with an overall F1-score of 0.93, demonstrating strong predictive performance.

Class	Precision	Recall	F1-score	Support
Existing Customer	0.81	0.73	0.77	327
Attrited Customer	0.95	0.97	0.96	1699
Accuracy			0.93	2026
Macro avg	0.88	0.85	0.86	2026
Weighted avg	0.93	0.93	0.93	2026

Table 2: Classification Report for ANN Model

3.3 Feature Importance

Analysis revealed the top features influencing churn prediction, in order of importance:

Avg_Open_To_Buy, Avg_Utilization_Ratio, Months_Inactive_12_mon, Dependent_count, Credit_Limit . This highlights the significance of customer behavior patterns, credit usage, and financial metrics in predicting churn. The model's focus on these features suggests that customer engagement, credit management, and personal financial situations are key indicators of potential attrition.

3.4 Discussion

The ANN model exhibited strong performance with a test accuracy of 93%. The high F1-scores for both classes, especially for Attrited Customers (0.96), indicate that the model is effective at predicting churn despite the class imbalance. The use of dropout layers and appropriate activation functions (ReLU in hidden layers, Sigmoid in the output layer) proved effective for this binary classification task.

4 Maternal Health Risk Dataset

Maternal health risk assessment is crucial for reducing mortality and morbidity, especially in developing countries. This study utilizes an IoT-based monitoring system dataset to classify maternal health risks, demonstrating the potential of machine learning in healthcare. Source: Hospitals and clinics in rural Bangladesh Size: 1,013 instances Features: Age, Blood Pressure, Blood Sugar, Body Temperature, Heart Rate Target: Risk Level (Low, Mid, High)

4.1 Dataset Characteristics and pre-processing

The Maternal Health Risk dataset, with only 1,013 instances, exemplifies the challenges of limited data classification. This scarcity of data can lead to: (1) Reduced model generalization. (2) Increased risk of overfitting. (3) Difficulty in capturing complex patterns, especially for mid-risk cases. In contrast, the larger Credit Card Churn dataset allowed for more robust model training data. Similar to the Credit Card Churn dataset, the Maternal Health Risk data underwent comprehensive preprocessing to optimize it for

4.2 ANN Model for Maternal Health Risk Classification

Please refer to the Jupyter Notebook for the structure analysis.

4.3 Model Training Performance

Initially, at epoch 10, the model achieved an accuracy of approximately 68%. By the final epoch, this improved to about 70%, indicating a modest but steady learning progression. The validation accuracy, while fluctuating throughout the training, showed an overall improvement from 63% to 66%. This slight gap between training and validation accuracies suggests mild overfitting, though not severe. **Note:** For a detailed class-wise analysis of the model's performance, including precision, recall, and F1-scores for each risk category (Low, Mid, High), please refer to the accompanying Jupyter notebook.

Table 3: Performance Metrics of ANN Model for Maternal Health Risk Prediction

Risk Level	Precision	Recall	F1-score	Support
High Risk	0.75	0.87	0.80	47
Low Risk	0.60	0.85	0.70	80
Mid Risk	0.74	0.34	0.47	76
Accuracy		0.67		203
Macro Avg	0.70	0.69	0.66	203
Iighted Avg	0.69	0.67	0.64	203

4.4 ANN Model Comparison

The ANN model for the Maternal Health Risk dataset differs in structure from the Credit Card Churn model, reflecting the unique challenges of each classification task:

Characteristic	Credit Card Churn Model	Maternal Health Model
Input Layer	23 features	6 features
Hidden Layers	3 (64, 32, 16 neurons)	3 (64, 32, 16 neurons)
Output Layer	1 neuron (Sigmoid)	3 neurons (Softmax)
Activation Functions	ReLU (hidden), Sigmoid (output)	ReLU (hidden), Softmax (output)
Dropout	Used (0.3 rate)	Used (0.3 rate)
Classification Type	Binary	Multi-class (3 levels)
Dataset Size	10,000 samples	1,013 samples
Best Accuracy	93%	70%
Key Challenge	Class imbalance	Limited data, multi-class

Table 4: Comparison of ANN Models: Credit Card Churn vs Maternal Health Risk

The Maternal Health model features a wide initial layer (64 neurons) with steep reduction and dropout for regularization, suited for fewer features and limited data. It uses softmax output for multi-class classification. The Credit Card Churn model employs gradual neuron reduction across more layers, reflecting its larger feature set and binary classification task.

4.5 Key Takeaways: Feature Scaling Impact and Dataset-Specific Challenges

Feature scaling, using the normalization formula $x_{normalized} = \frac{x - x_{min}}{x_{max} - x_{min}}$, was crucial for both datasets. It improved training convergence, balanced feature importance, and mitigated dominance of larger-magnitude features. Credit Card Churn dataset faced binary classification with imbalanced classes (16.07% churn rate), but benefited from a rich feature set and larger size, allowing better generalization. Maternal Health dataset involved multi-class classification with varying risk level representation. Its limited features and smaller size challenged the model's discriminative power and increased overfitting risk, especially for the under-represented mid-risk class.

5 Conclusion

This comparative study highlights the significant impact of dataset size and complexity on ANN performance in classification tasks. While the Credit Card Churn model demonstrated strong performance with a larger, more complex dataset, the Maternal Health Risk model faced challenges typical of limited data scenarios. The application of feature scaling proved beneficial for both datasets, enhancing the models' ability to learn from the data effectively. However, the stark difference in performance underscores the need for specialized techniques when dealing with limited data, particularly in critical domains like healthcare.

References

[1] C. Li, J. Wang, L. Wang, L. Hu and P. Gong, "Comparison of Classification Algorithms and Training Sample Sizes in Urban Land Classification with Landsat Thematic Mapper Imagery," *Remote Sensing*, vol. 6, no. 2, 2014.