



# HiLCoE

School of Computer Science  
& Technology

## *Group Report on Machine Learning*

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## 1. Introduction

The objective of this project is to build, train, and evaluate a Neural Network classification model to predict the severity of road traffic accidents based on a dataset from Addis Ababa. The target variable, *Accident Type*, classifies accidents into four categories: **Fatal**, **Serious Injury**, **Minor Injury**, and **Property Damage Only (PDO)**.

This report summarizes the end-to-end workflow, from Exploratory Data Analysis (EDA) and rigorous data cleaning to model architecture design and final performance evaluation.

## 2. Data Understanding and Preparation

### 2.1. Exploratory Data Analysis (EDA)

Initial analysis revealed significant data quality challenges. The raw dataset contained over 30 features, but many suffered from high rates of missing values.

- **Missing Data:** Columns such as *Zone*, *Region*, and specific victim details (e.g., *Victim-2 Movement*) had missing rates exceeding 70%.
- **Class Imbalance:** The target variable was heavily skewed. **Minor Injuries** accounted for approximately 63% of the data, while **Fatal** accidents represented only 3%.

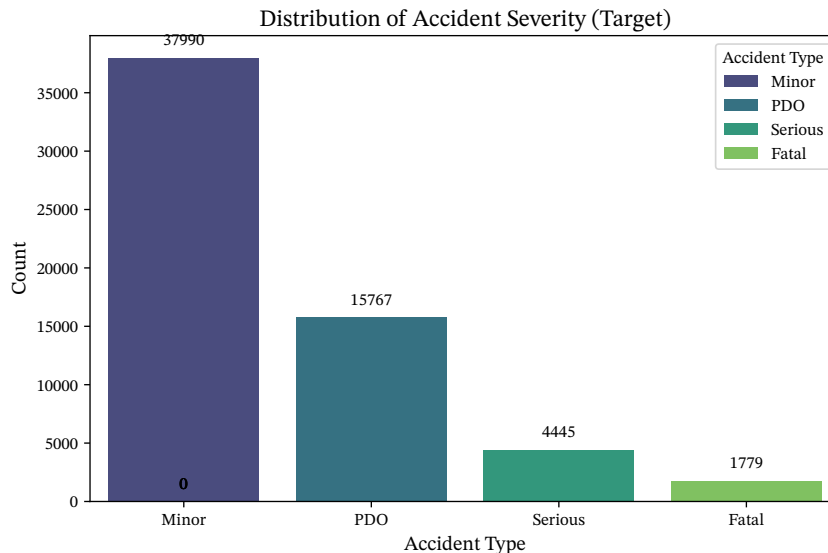


Figure 2: Distribution of Accident Severity (Target Variable). Note the severe imbalance.

### 2.2. Data Cleaning & Standardization

Before modeling, a custom cleaning pipeline was implemented:

1. **Standardization:** Typos were corrected (e.g., “Augest” → “August”, “Privategg” → “Private”). Amharic terms like “Amet” (Year) and “Wor” (Month) were standardized.
2. **Outlier Removal:** Impossible values (e.g., Driver Age > 90, Experience > 60 years) were treated as missing.
3. **Feature Dropping:** Columns with > 70% missing data were removed to reduce noise.

### 2.3. Feature Engineering & Preprocessing

To prepare the data for the Neural Network:

- **Cyclical Encoding:** The time of day was converted from linear hours (0-23) into sine and cosine components to preserve the temporal proximity between 23:00 and 00:00.
- **Imputation:** Median imputation was used for numerical features (e.g., Age) and Mode imputation for categorical features.
- **Scaling & Encoding:** Numerical features were standardized using *StandardScaler*. Categorical variables were transformed using *OneHotEncoding*.

### 3. Model Design

#### 3.1. Architecture

A Multi-Layer Perceptron (MLP) was designed using TensorFlow/Keras. The architecture features a “funnel” design to compress high-dimensional inputs into abstract representations.

- **Input Layer:** 230 features (resulting from One-Hot Encoding of high-cardinality categorical variables).
- **Hidden Layer 1:** 128 Neurons, ReLU activation, Batch Normalization (Param count: 29.5k).
- **Hidden Layer 2:** 64 Neurons, ReLU activation, Batch Normalization (Param count: 8k).
- **Output Layer:** 5 Neurons with Softmax activation.

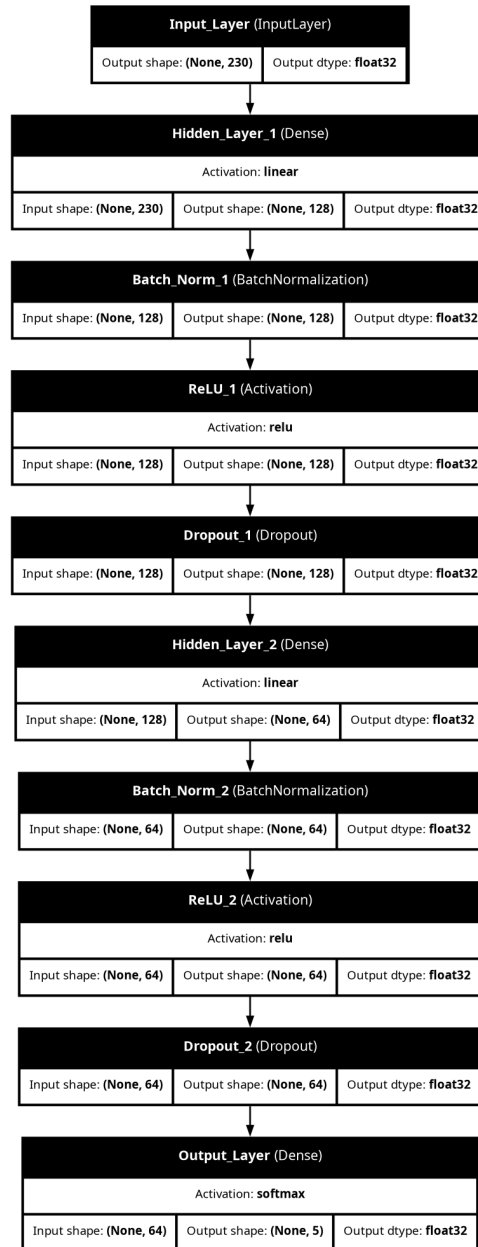


Figure 3: Neural Network Architecture Diagram. Total trainable parameters: 38,533.

#### 3.2. Design Justification

- **ReLU Activation:** Selected to prevent the vanishing gradient problem.
- **Dropout (0.3 - 0.4):** Applied after hidden layers. Given the high dimensionality (230 features), dropout was crucial to prevent the model from memorizing specific input patterns.
- **L2 Regularization:** Added to penalize large weights, keeping the model weights small and stable.

## 4. Training Process

The model was trained for up to 100 epochs using the **Adam** optimizer. To address the class imbalance identified in EDA, **Class Weights** were computed and applied to the Loss Function. This penalizes the model more heavily for misclassifying rare classes (Fatal/Serious) than common ones (Minor).

### Overfitting Mitigation:

- **Early Stopping:** Training halted automatically when Validation Loss failed to improve for 15 epochs.
- **Model Checkpointing:** Only the model version with the highest Validation Accuracy was saved.

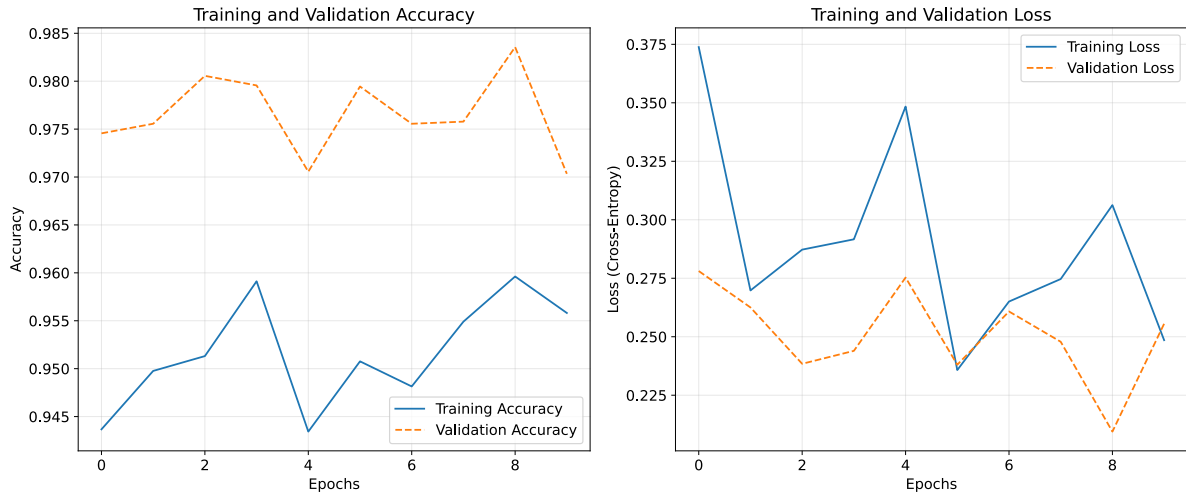


Figure 4: Training and Validation Performance Curves. Note the convergence point where Early Stopping triggers.

## 5. Evaluation and Interpretation

### 5.1. Performance Metrics

The model was evaluated on an unseen Test Set. The performance was exceptional, achieving an overall accuracy of approximately **98%**.

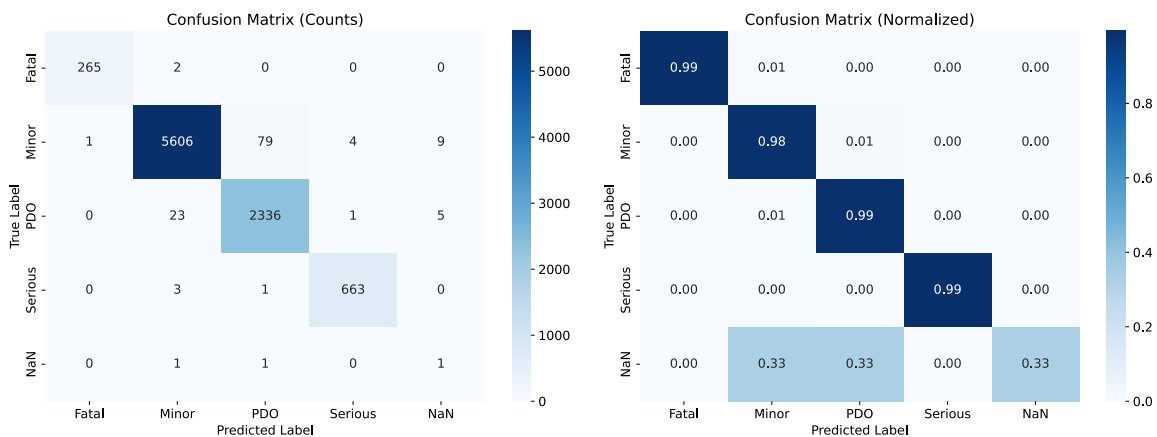


Figure 5: Confusion Matrix. Note the near-perfect diagonal, indicating high classification accuracy across all classes.

### 5.2. Analysis of Results

#### 1. Strengths:

- **High Recall on Fatal Cases:** The model correctly identified 265 out of 267 fatal accidents (99% Recall). This is a significant achievement, as “Fatal” is usually the hardest class to predict due to its rarity.
- **Robustness:** The validation loss remained stable alongside training loss, indicating that the regularization techniques effectively prevented overfitting despite the model’s high capacity.

## 2. Critical Reflection (Data Insights):

- Upon analyzing the feature importance, the high accuracy suggests the model utilized strong predictors present in the dataset, specifically the **post-accident** casualty counts (e.g., `Number of fatalities`, `Number of severe injuries`).
- Since the target variable (`Accident Type`) is directly derived from these counts, the model effectively learned the rule-based definitions of the categories (e.g., if `Fatalities > 0`, then `Type = Fatal`).
- While this makes the model a highly effective **classifier** for historical records, it relies on data that would not be available before an accident occurs.

## 6. Recommendations & Conclusion

### 6.1. Potential Improvements

1. **Predictive Modeling:** To build a model that predicts severity **before** an accident happens (based purely on road conditions, weather, and driver demographics), a second iteration of this project should explicitly exclude the `Number of fatalities/injuries` columns from the input.
2. **Advanced Architectures:** For the predictive (non-leakage) version, implementing **TabNet** or **Wide & Deep** networks would be necessary to capture complex interactions between environmental factors without relying on casualty counts.

### 6.2. Conclusion

The project successfully demonstrated the end-to-end Neural Network workflow. The data preparation phase successfully transformed a messy dataset into a clean, 230-feature input space. The resulting model achieved 98% accuracy in classifying accident severity, proving that the Neural Network can effectively map input features to accident outcomes when casualty data is available.

### 6.3. Reflection on Workflow

The project demonstrated that **Data Preparation** is the most critical phase. The raw data required extensive cleaning before any modeling could succeed. The transition from a raw, noisy Excel sheet to a structured Neural Network pipeline highlights the importance of robust feature engineering (like cyclical time encoding) and rigorous evaluation beyond simple accuracy.