**Technology Design Project – COS 60011**

**Deliverable 1**

**Individual Research Report**

**Name:** Arun Ragavendhar Arunachalam Palaniyappan

**Student ID:** 104837257

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Acknowledgment to country and references)

# Acknowledgement to Country

The contemporary day Melbourne and Swinburne University of Technology are located in what was once known as the Kulin Nation. As a Swinburne student who is deeply thankful and happy to be studying at this prestigious university, I would want to sincerely express my respects to the Wurundjeri People of this nation, who are the traditional proprietors of these lands. In addition, I gratefully acknowledge Swinburne's Aboriginal and Torres Strait Islander students, alumni, partners, and guests. It is an honour and a source of pride for me to recognise and appreciate the spirituality, history, and culture of this location with the Wurundjeri land.

# 1. Introduction

Machine learning (ML) is a groundbreaking method that allows computers to learn from data and make judgements without requiring explicit programming. Many current applications rely on machine learning, particularly recommendation algorithms, which are critical in directing user choices across a wide range of areas, from movies and books to products and services.

This report focuses on the learnings and knowledge acquired through research, for the implementation of a car recommendation system using a Deep Feedforward Neural Network, also known as a Multi-Layer Perceptron (MLP). The report will cover the basics of machine learning and neural networks, delve into the specifics of deep MLPs and backpropagation, and outline the steps involved in implementing this model in a recommendation system. **(Alpaydin,2020).**

# 2. Machine Learning and Neural Networks

## 2.1 Understanding Machine Learning

Machine learning is a subset of artificial intelligence (AI) in which algorithms use data to generate predictions or judgements. The major objective is to enable computers to automatically detect patterns in data and improve over time. There are three main types:

• **Supervised Learning:** The model is trained using labelled data with known input-output pairings. The goal is to learn a mapping of inputs to outcomes.

• **Unsupervised learning:** This involves training models on unlabelled data to find patterns or groups.

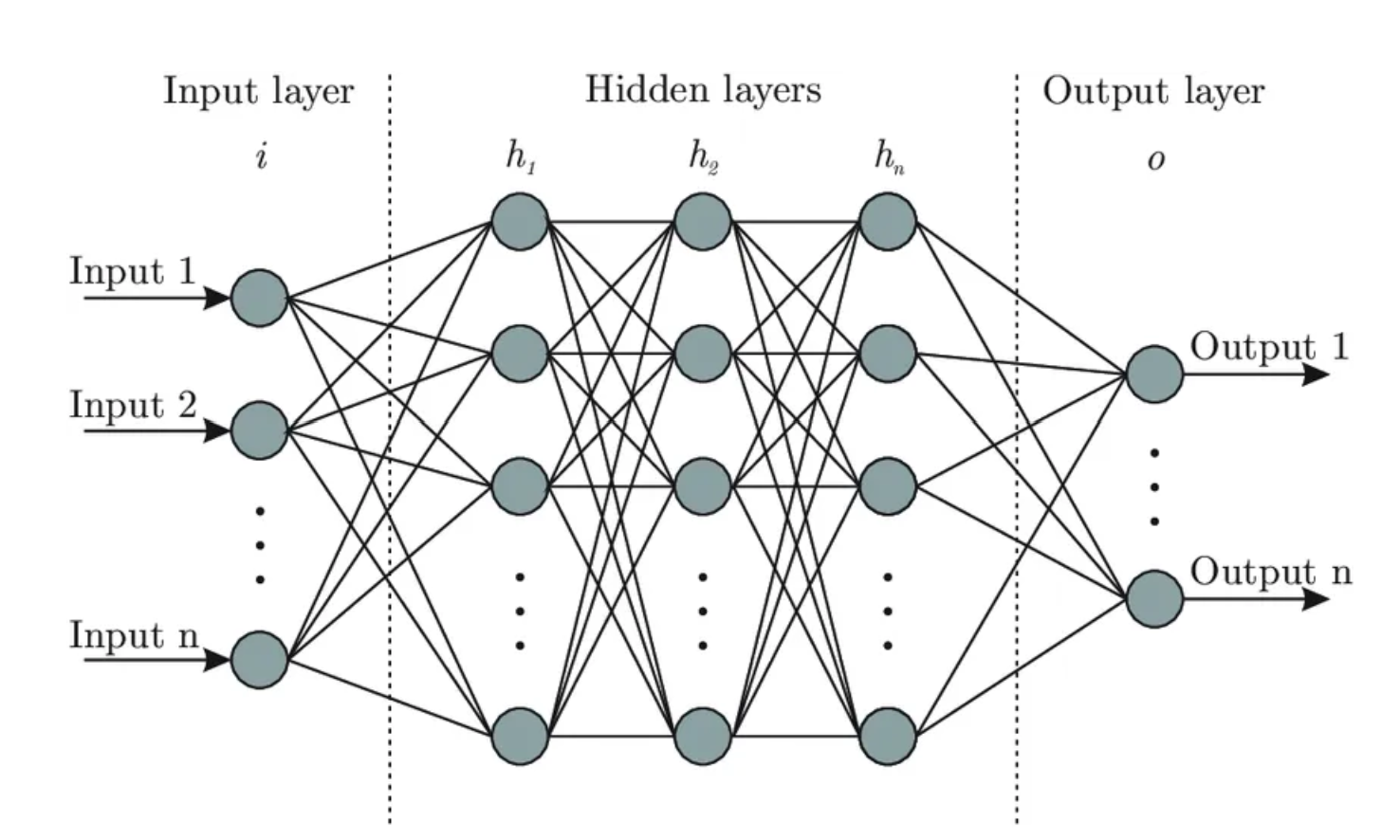
• **Reinforcement learning:** The model learns through interactions with its surroundings, receives feedback, and improves its performance.

For the proposed project**, supervised learning** is to be used to predict car recommendations based on user preferences and requirements.

## 2.2 Introduction to Neural Networks

Neural networks are computer models that draw inspiration from the structure and function of the human brain. They are made up of layers of linked nodes, or neurons, that process information via a network of weighted connections. **(Nielsen,2015).**

Figure 1: Basic Structure of a Neural Network - **(Sutskever et al., 2011).**



• The **input layer** receives raw data characteristics (such as the car attributes).

• **Hidden layers** are intermediate levels where data undergoes complicated changes. The network becomes deeper as the number of hidden levels increases.

• The **output layer** generates the ultimate result, in this example, the final suitable car suggestions.

Each connection between neurons has an associated weight, and each neuron has an activation function that determines whether it should "fire" or pass on its signal. The learning process involves adjusting these weights to minimize the difference between the predicted output and the actual target. **(Sutskever et al., 2011).**

# 3. Deep Feedforward MLP with Backpropagation

## 3.1 Core Fundamentals

A Deep Feedforward MLP is a neural network in which the connections between neurons do not generate cycles. Data travels in a single direction: from the input layer to the output layer, via numerous hidden layers. (**Zhang et al.,2021).** The network's depth (the number of hidden layers) enables it to detect complicated patterns in the data.

## 3.2 Backpropagation

Backpropagation comprises two primary phases: forward pass and backwards pass.

**Forward Pass:** The input data is sent through the network layer by layer until it reaches the output layer, when a prediction is formed.

**Backwards Pass:** The error between the expected and actual outputs is determined. This mistake is then transmitted back across the network, and the weights are changed to reduce the error.

The backwards pass is based on a mathematical concept known as gradient descent, which seeks a function's minimum by iteratively travelling in the direction of steepest fall.

## 3.3. Mathematical Representation of the Model

### 3.3.1. Forward Pass Equation

**Equation:**

**Explanation:**

* **(Predicted Output):** This is the output predicted by the model, also called the model's prediction.
* **(Weights Matrix):** In a neural network, each input feature is multiplied by a weight. The weights determine the importance of each input feature in making predictions.
* **(Input Features):** This represents the features or data points that are input into the model.
* **(Bias Term):** This is a constant that allows the model to fit the data better by shifting the activation function.
* **(Activation Function):** This function applies a non-linear transformation to the input. Common activation functions include:
  + **(Rectified Linear Unit):** Outputs zero if the input is negative and outputs the input itself if it's positive.
  + **:** Squeezes the input into a range between 0 and 1. **(Chollet,2017).**

**How it works:**

* The input features are multiplied by the corresponding weights , and the bias is added to the result. This linear combination ) is then passed through the activation function to introduce non-linearity, resulting in the predicted output .

### 3.3.2. Loss Function (Cross-Entropy Loss)

**Equation:**

**Explanation:**

* **(Loss Function):** The difference between the predicted output ^​ and the actual output is calculated by the loss function. The core aim is to minimize this loss to improve the model’s accuracy.
* **(Actual Output):** This is the true label or value that is to be predicted.
* **​ (Predicted Output):** This is the output predicted by the model.

**How it works:**

* **Cross-Entropy Loss** is used primarily in classification problems. It quantifies how far the predicted probabilities () are from the actual labels (​).
* The equation sums over all classes . For each class , it multiplies the actual label ​). by the logarithm of the predicted probability ​). **(Goodfellow et al.,2016).**
* If the predicted probability ​) is close to the actual label ​), the loss will be small. If it's far off, the loss will be large. The aim of training is to reduce this loss.

### 3.3.3. Gradient Descent Update Rule

**Equation:**

**Explanation:**

* **(Updated Weights):** These are the new values for the weights after the update.
* **(Current Weights):** These are the weights before the update.
* **(Learning Rate):** This is a small positive value that controls the step size of the update. It dictates on how quickly or slowly the model learns. **(Russell et al.,2021).**
* **(Gradient of the Loss with Respect to Weights):** This represents the slope of the loss function with respect to the weights. It tells us how to change the weights to decrease the loss.

**How it works:**

* **Gradient Descent** is an enhancement algorithm used to reduce the loss function.
* The algorithm updates the weights in the direction that decreases the loss.
* The term ​ (the gradient) points in the direction of the steepest ascent of the loss function. By subtracting it, we move the weights in the direction of the steepest descent (hence minimizing the loss). **(Murphy et al.,2012).**
* The learning rate controls how large of a step we take in that direction. If is too large, it might overshoot the minimum; if it’s too small, learning will be slow.

## 3.4. One-hot Encoding Model

One-hot encoding is a way to convert categorical data (like car brand, fuel type, or body type) into a format that a machine learning model can easily understand. **(Bishop,2006).** For example, for a set of different car brands: Toyota, Honda, and Ford; One-hot encoding turns each brand into a unique row of binary values (0s and 1s), as given below:

* Toyota: [1, 0, 0]
* Honda: [0, 1, 0]
* Ford: [0, 0, 1]

This ensures the neural network treats each brand as distinct, avoiding any false numerical relationships. In a car recommendation system, one-hot encoding enables the deep

feedforward MLP to accurately process features like car brands, fuel types, and body styles, leading to better pattern recognition and more accurate recommendations.

Table 1: One-hot encoding model of Car brand, fuel type and car body type of a car dataset **(Bishop,2006).**

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Price | Honda | Toyota | Ford | Diesel | Petrol | Hatchback | SUV | Sedan |
| 25000 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 1 |
| 27000 | 0 | 1 | 0 | 1 | 0 | 0 | 1 | 0 |
| 22000 | 1 | 0 | 0 | 0 | 1 | 1 | 0 | 0 |
| 24000 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 1 |
| 26000 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 0 |
| 23000 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 0 |

# 4. Implementation of the Car Recommendation System

## 4.1. Data Preparation

The dataset is prepared by one-hot encoding categorical variables and normalising numerical data to guarantee consistent scales and improved model performance.

## 4.2. Model Initialisation

A deep Multi-Layer Perceptron (MLP) is configured with a specific architecture that contains layers and activation functions designed to handle input efficiently.

## 4.3. Training

Using backpropagation and gradient descent, the model learns to predict properly and adjusts its weights to reduce the disparity between its predictions and actual outcomes.

## 4.4. Deployment

The trained model is planned to be deployed into a Streamlit web application, where users can enter their vehicle preferences and receive personalised car recommendations. **(Smith et al.,2021).**

# 5. Summary and Conclusion

This research report investigated the use of **a Deep Feedforward Multi-Layer Perceptron (MLP) with one-hot encoding model** to create a **Car recommendation system**. By covering the fundamentals of machine learning and neural networks, it discussed the MLP's design and training procedure, emphasising the importance of one-hot encoding in categorical data processing.

The report emphasises on the efficient use of backpropagation and gradient descent algorithms to improve the model's performance. The trained final model is planned to be integrated into a Streamlit web application to provide users with personalised car recommendations based on their tastes. In conclusion, the research confirms deep learning's effectiveness in handling complex data for recommendation systems, with significant implications for enhancing personalized recommendations in future applications.

# 7.Appendix

## 7.1 List of Figures

**Figure 1**: Basic Structure of a Neural Network

## 7.2 List of Tables

**Table 1**: One-hot encoding model of Car brand, fuel type and car body type of a car dataset

# 8. References

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