COS 60011 – Technology Design Project

Deliverable 4

Final Project Report

AI Car Purchase Recommendation System

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Acknowledgement to Country

As a student at Swinburne University of Technology, I am profoundly grateful for the opportunity to study on the ancestral land of the Kulin Nation, where the city of Melbourne now stands. I extend my sincere thanks to the Wurundjeri People, who are the traditional custodians of this land. I also acknowledge with respect the Aboriginal and Torres Strait Islander students, alumni, collaborators, and visitors who are part of the Swinburne community. It is an honour to recognize and appreciate the rich spiritual, historical, and cultural legacy of the Wurundjeri land, which inspires both respect and pride.

Executive Summary

The AI Car Purchase Recommendation System was developed to address the often-overwhelming process of choosing a car, where buyers must balance various features such as budget, brand value, fuel efficiency, and safety. With many existing car recommendation platforms relying on basic filters, users frequently receive suggestions that don't fully align with their unique needs. The main aim of this project was to solve this, using a machine-learning-based recommendation system that offers personalized car suggestions by analysing a user's specific preferences.

The core of this project is a custom Multi-Layer Perceptron (MLP) neural network model built in TensorFlow, trained on a dataset of 10,000 car records covering 18 attributes—including key factors like body type, engine type, and user ratings. The model was carefully designed and fine-tuned using methods such as Dropout and Batch Normalization to avoid overfitting, with Early Stopping implemented to optimize training time. Through rigorous evaluation, the model achieved a high-test accuracy of 90.86%, providing reliable recommendations tailored to user input.

An intuitive front-end interface, developed with Streamlit, allows users to interact with the system through simple, image-based selection options, enhancing the user experience and making advanced AI technology accessible even to non-technical users. The system presents recommendations in a clear and engaging format, bridging complex machine learning with a user-friendly design.

This project showcases the potential of AI-driven tools in simplifying decision-making and personalizing the car-buying journey. Looking forward, the system has the potential to expand into a cloud-deployed solution or an API for seamless integration with other platforms. It could also be developed into a mobile app for users on the go.

This project report not only demonstrates the power of AI in enhancing decision-making but also serves as a valuable learning experience in bridging technical system design and user-centred interface design. Through the challenges of developing a neural network from scratch, managing data complexities, and creating an intuitive interface, the project reinforced the importance of combining rigorous technical methods with a focus on accessibility. This approach to learning and adapting new skills in machine learning, data processing, and user experience design lays a strong foundation for future AI projects, ensuring they are both impactful and user-friendly.

Contents

Abbreviations

ML: Machine Learning
AI: Artificial Intelligence
UI: User Interface
API: Application Programming Interface
MLP: Multi-Layer Perceptron
DL: Deep Learning
K-Fold: K-Fold Cross-Validation
SMOTE: Synthetic Minority Over-sampling Technique
RMSprop: Root Mean Square Propagation
ReLU: Rectified Linear Unit
L2: L2 Regularization
NLP: Natural Language Processing
CSV: Comma-Separated Values
GPU: Graphics Processing Unit
PCA: Principal Component Analysis
MSE: Mean Squared Error
TF: TensorFlow
ROC: Receiver Operating Characteristic
AUC: Area Under the Curve

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1. Introduction

1.1 Project background and motivations

Need for a Car Recommendation System

Choosing the right car has become increasingly complex, with buyers needing to consider a wide range of options and features, such as budget, brand reputation, safety, and comfort. This abundance of choices often makes the decision-making process overwhelming for buyers, who may struggle to identify the best fit for their specific needs. The goal of this project was to develop an AI-powered Car Purchase Recommendation System that simplifies this process by providing personalized car suggestions. This system was designed to save users time and help them make confident, informed choices tailored to their preferences.

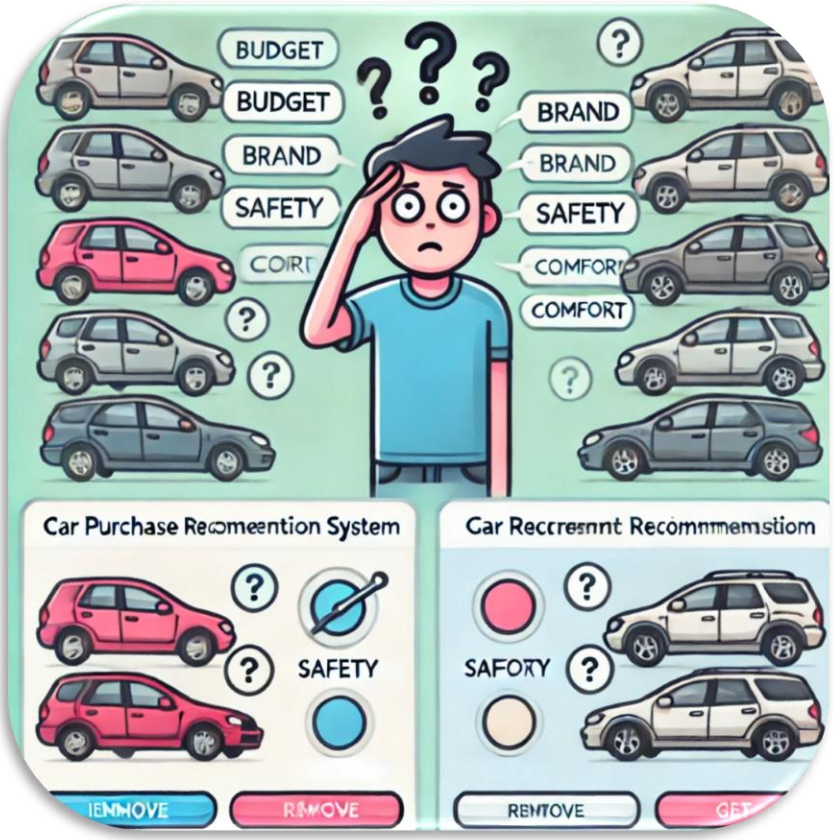

Figure 1: Image showing a confused car buyer overwhelmed by excess data

Advantages of a Neural Network based Recommendation system

Unlike traditional platforms, this project employed an advanced Multi-Layer Perceptron (MLP) neural network integrated with an interactive web application. This approach not only enhanced user engagement but also delivered real-time, personalized recommendations based on each user's specific preferences. By analysing and interpreting complex inputs, the system streamlined the car selection process, making it faster, more intuitive, and tailored to the unique needs of individual users **[8]**.

Figure 2: Image representing an MLP Neural Network

Reason for Choosing a Custom Self-Made Neural Network Model Instead of an Existing LLM API

In this project, a custom-built Multi-Layer Perceptron (MLP) neural network model was chosen over an existing large language model (LLM) API for several key reasons. Firstly, the custom model allowed to design a system that directly addressed specific car features and user preferences without the extra complexity often present in generalized models like LLMs **[1]**. This tailored design improved efficiency by focusing only on relevant attributes, such as budget, safety, and performance, leading to quicker and more accurate recommendations.

Additionally, building a custom model provided full control over data handling, training parameters, and optimization techniques, which was essential for fine-tuning the system to deliver reliable results. Using a pre-built LLM API would have restricted this level of control, making it difficult to optimize for such a specialized use case **[1]**.

From a cost and resource perspective, the custom model proved more sustainable, as it avoided the recurring costs associated with API calls to third-party services.

Lastly, building a new neural network from scratch also helped in achieving a deeper and more hands-on learning experience, something which a pre-existing LLM cannot possibly provide.

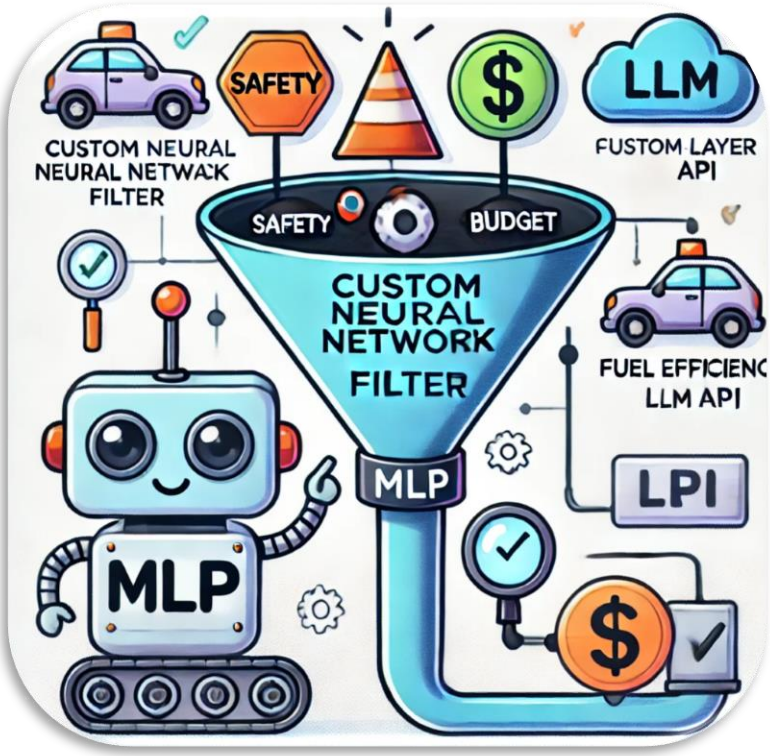

Figure 3: Image representing a custom neural network over an LLM

1.2 Project description and Scope

The goal of this project was to develop an interactive web application powered by a custom-designed Feedforward Multi-Layer Perceptron (MLP) neural network model with backpropagation. This model was created to predict and recommend the most suitable car for a user based on their specific preferences. The project aimed to address the limitations of existing car recommendation platforms, which often rely on basic filters and fixed algorithms that fail to deliver personalized suggestions adapted to individual user needs.

To achieve a more tailored and dynamic recommendation system, a neural network model was designed and implemented from scratch, enabling precise control over training, data handling, and performance tuning. Unlike using an external large language model (LLM) API—which could introduce additional costs and complexities—this custom-built model allowed for flexibility and customization, ensuring it could effectively analyze a wide range of car attributes and user preferences to provide accurate recommendations **[1]**.

The model was seamlessly integrated into a user-friendly web application developed using Streamlit. This interface facilitated an engaging user experience, where individuals could input their preferences through a series of interactive questions and receive real-time, personalized car recommendations. The design emphasized ease of use, making the application accessible to users with varying levels of technical knowledge **[12]**.

This report covers the entire project process, including the implemented design, testing, debugging, and analysis of real-world user test results. Additionally, it reflects on the insights gained, aligned

with the unit learning outcomes, highlighting technical and personal growth throughout the project. This comprehensive approach offers a clear view of the structured and collaborative efforts that contributed to the successful delivery and live demonstration of the final solution.

2. Review on Existing Car Recommendation systems in the Market and their limitations

2.1 Review of Existing Systems

Current car recommendation platforms, including popular sites like **CarWow, Cars24.com, and Autocar.com**, aim to simplify car selection by allowing users to just filter and search based on common features. These platforms typically rely on simple SQL filters or algorithms like cosine similarity, which match user preferences to car attributes, such as budget, fuel type, or brand. While these tools provide basic sorting and filtering, their approach to recommendations remains relatively static, inflexible and extremely basic **[4]**.

For instance, platforms may allow users to apply filters to narrow down car options, presenting results based on fixed criteria (e.g., listing cars within a specified price range or of a certain fuel type). Additionally, some platforms use similarity metrics like cosine similarity to compare and rank cars based on shared characteristics **[3]**. This method can suggest cars with similar attributes, but it lacks adaptability in handling complex, multi-faceted user needs. Thus, these existing systems serve primarily as catalogues or directories, offering a more generic, rule-based selection rather than a personalized recommendation.

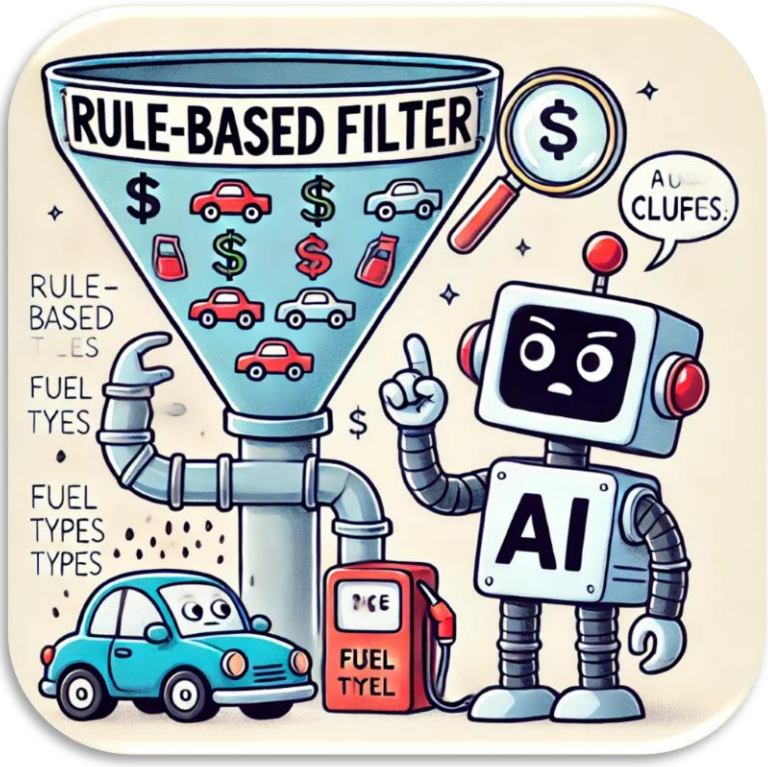

Figure 4: Image representing a simple rule-based filter

2.2 Limitations of Current Systems

Despite their usefulness as car search engines, existing recommendation systems face notable limitations in meeting individual user needs. The primary shortcoming lies in their dependence on fixed filters and rigid algorithms that lack the capability to learn from and adapt to individual user preferences over time. Most of these platforms do not incorporate machine learning or AI models that could dynamically tailor recommendations based on diverse, unique user input.

As a result, users are often unable to receive suggestions that consider multiple criteria simultaneously, such as balancing budget, brand value, performance, and safety—preferences that may vary significantly from one buyer to another. The limitations are especially apparent for niche requirements, where users may look for specific combinations of features, like a compact electric car with high safety ratings and low maintenance costs. Existing systems rarely accommodate such nuanced preferences, leaving users with recommendations that may align only partially with their needs. Ultimately, this limits the ability of these platforms to provide a personalized, context-aware experience that can guide users in making more informed decisions based on their unique circumstances.

The primary reason for doing this project is to offer an effective and long-term solution to the above-mentioned limitations.

2.3 Individual Contributions

Arun Ragavendhar Arunachalam Palaniyappan (104837257) – *(Group Leader, Lead Software Developer, Researcher, Machine Learning Engineer, Data Engineer)*

I led the project, guiding its direction and coordinating efforts to ensure all components aligned with the goal of creating a personalized car recommendation system. As the Data Engineer, I was responsible for creating and preparing the dataset, which involved gathering, cleaning, and organizing data on car features to ensure a robust foundation for the model.

In my role as Machine Learning Engineer, I designed and developed the Multi-Layer Perceptron (MLP) neural network model using TensorFlow. I meticulously fine-tuned the model, enabling it to accurately analyze user inputs and deliver personalized recommendations.

Additionally, I developed the interactive web application using Streamlit. This interface allowed users to input their preferences through intuitive, clickable image options, enhancing the user experience. I also ensured seamless integration between the interface and the neural network, enabling real-time, customized recommendations.

Overall, my contributions consisted of data creation, cleaning and preparation, model development, and application design, covering all major aspects of the project from start to finish.

3. Design Concept and Project Implementation

3.1 Problem Statement and Proposed Solution

Selecting the right car has become challenging for buyers due to the vast variety of models, features, and price points. Factors such as budget, brand, safety, fuel efficiency, and comfort add layers of complexity to the decision-making process. As discussed earlier, traditional car recommendation platforms often fall short of providing tailored suggestions, relying instead on basic filters and static algorithms that fail to account for individual needs. This results in recommendations that lack the depth, context of use and personalization buyers seek.

To address this gap, the project developed a custom Multi-Layer Perceptron (MLP) neural network model integrated into an interactive web application. Trained on a comprehensive dataset, the model analysed car features and user preferences to deliver personalized recommendations. Unlike standard systems, this approach used each user's input across various criteria—like budget and performance—to generate tailored car suggestions in real-time. The interactive web app allowed users to easily select preferences, receive immediate feedback, and refine their choices, making the car-buying process more efficient, intuitive, and personalized.

3.2 Components of the system

The AI Car Purchase Recommendation System was built using three main parts:

1. **Front-End Web Application**: The user interface was created with Streamlit, a powerful and feature rich python library that makes it easy to build interactive web apps. This part of the system allowed users to enter their car preferences through a series of straightforward questions. Using clickable images and a user-friendly layout, the front end provided a simple, engaging way for users to explore car options and receive instant recommendations **[11,12].**
2. **Neural Network Model**: The recommendation engine itself is powered by a custom-built neural network created in TensorFlow. This model analyses the user's input and matches it with the best car options based on specific features. By using advanced learning techniques, the neural network can understand complex patterns, helping it provide recommendations that suit each person's unique needs **[1,8]**.
3. **Dataset for Training**: To make accurate recommendations, the neural network was trained on a dataset containing important car details, like type, fuel efficiency, price, customer ratings, etc. This dataset was carefully cleaned and prepared, so the model could learn the relationships between different car features and user preferences. This data-driven approach helped ensure that the recommendations were both reliable and personalized **[6]**.

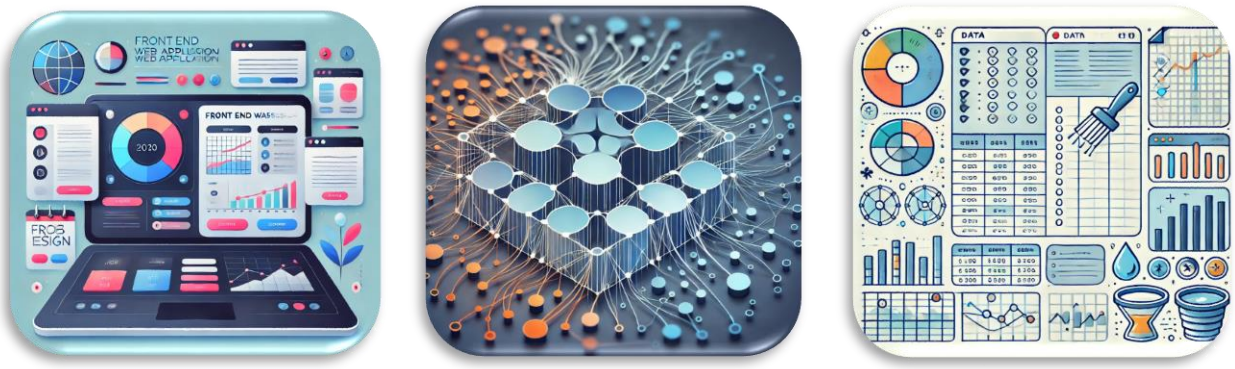

Figure 5: Image representing the 3 different components of the system

3.3 Front End Web Application

- The AI Car Purchase Recommendation System uses Streamlit, a powerful Python library, to create an engaging web application.
- The interface is designed to be interactive and visually appealing.
- Instead of dropdowns or sliders, the app features clickable buttons with images for each option **[12]**.
- This setup allows users to easily view and select their preferences with a single click, making the experience more interactive and user-friendly.

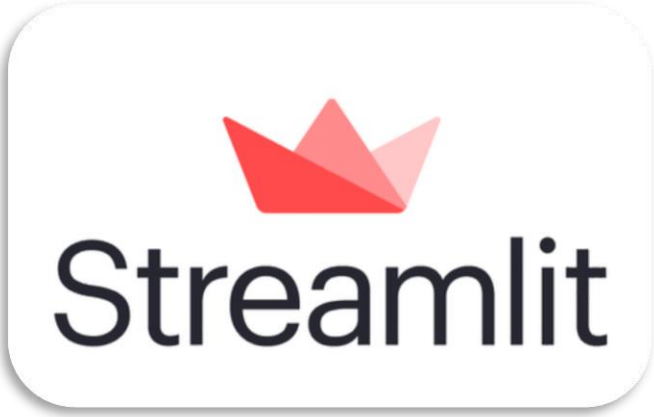

Figure 6: Streamlit Web Application Library

Detailed Breakdown of Pages and Questions

Page 1 (Questions 1-4):

- Users are asked about their preferred car body type, engine type, budget, and year of manufacture. Each question displays four clickable image options, clearly labeled and accompanied by intuitive graphics.

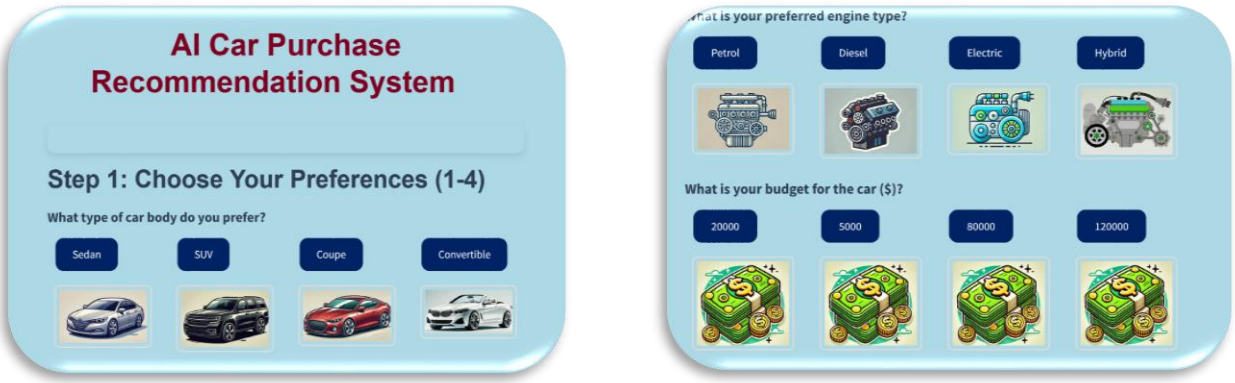

Figure7: Questions 1-4 on the Streamlit Web Application

Page 2 (Questions 5-8):

- Users are prompted to select their preferred transmission type, expected resale value, desired fuel economy, and preferred performance rating. As before, each option is visually represented, making the selection process both engaging and clear.

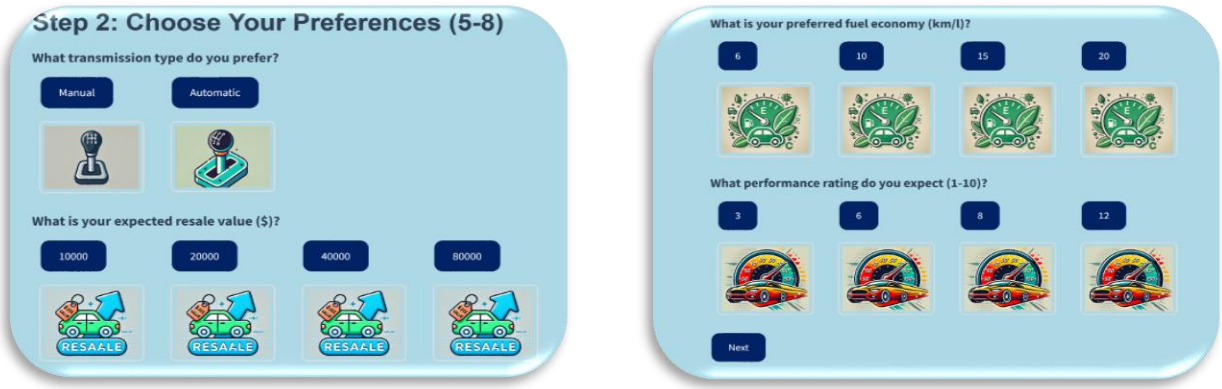

Figure 8: Questions 5-8 on the Streamlit Web Application

Page 3 (Questions 9-12):

- Users are guided through choosing their preferred user rating, safety rating, desired comfort level, and acceptable maintenance cost. Again, each option is a clickable graphic.

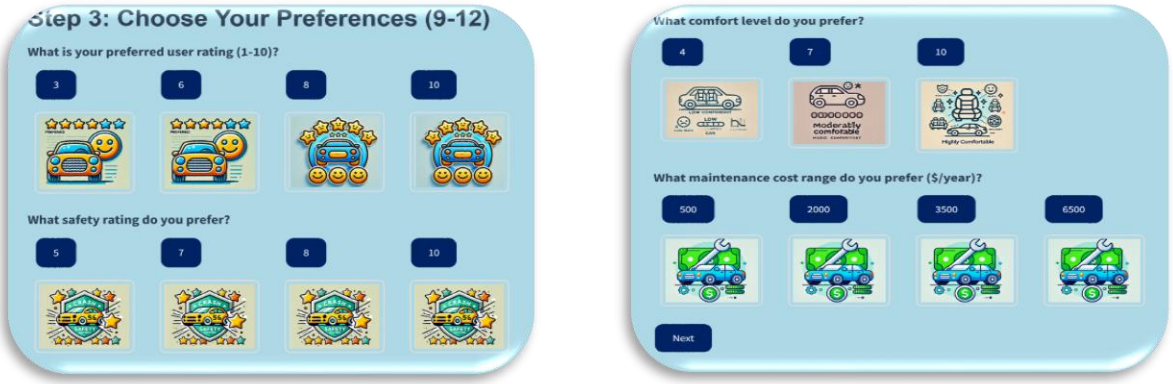

Figure 9: Questions 9-12 on the Streamlit Web Application

Page 4 (Questions 13-16):

- The final page asks users about their preferred warranty period, seating capacity, battery capacity (if relevant), and drive type. Once all selections are made, users are presented with a **"Submit" button** to finalize their response.

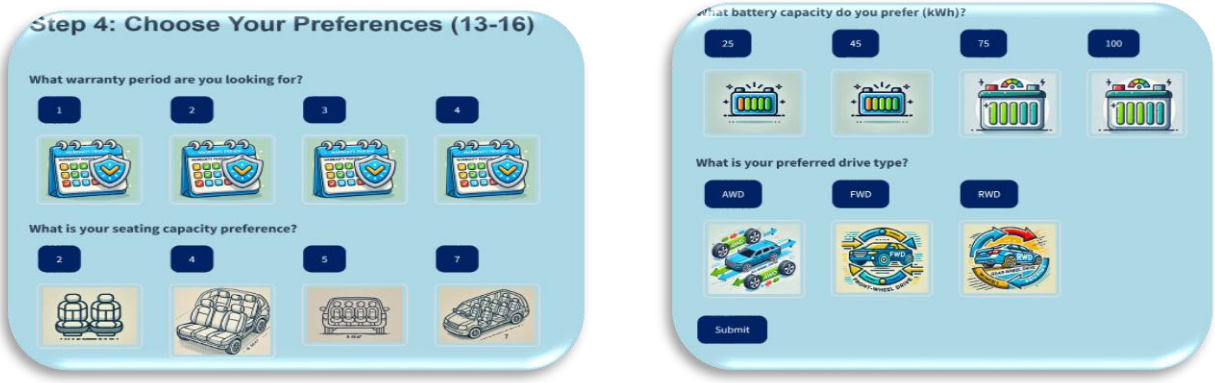

Figure 10: Questions 13-16 on the Streamlit Web Application

Collecting and Preparing User Responses for Model Input

- After the user completes all four pages and presses the **'SUBMIT'** the app collects the chosen options of the user and stores them in an array.
- Numerical inputs (like budget and fuel economy) are normalized using a technique called **Min-Max Scaling**, which scales all numbers between 0 and 1 **[9]**.
- This prevents any single feature from disproportionately influencing the model.
- Categorical responses (like body type and engine type), which are initially stored as string values, are transformed using **One-Hot Encoding** technique to match the specific input format expected by the neural network **[6]**.
- This encoding converts categorical options into binary vectors (e.g., [1, 0, 0, 0] for a "Sedan" in the "Body Type" category).

Personalized Car Recommendation and Confirmation

- Once the user responses are processed, the app feeds the data into the trained neural network model.
- The model analyzes the inputs and identifies the car that best aligns with the user's preferences.
- The car with the highest prediction probability is presented to the user with a personalized message.

- The app displays**: *"Hi buddy! here is my personalized recommendation for you! The most suitable car for you would be Hyundai Ioniq***
- This message not only confirms the recommendation but also creates a friendly and engaging experience for the user.

Figure 11: The recommended car being displayed to the user

Review and Verification of User Choices

- After receiving the car recommendation, if the user clicks **"Submit"** again, the app redirects them to a review page.
- This page presents a detailed summary of the user's chosen preferences in a neatly formatted table.
- Each row in the table corresponds to a question, with the selected option clearly listed beside it. This layout makes it easy for users to verify their selections before making a final decision.

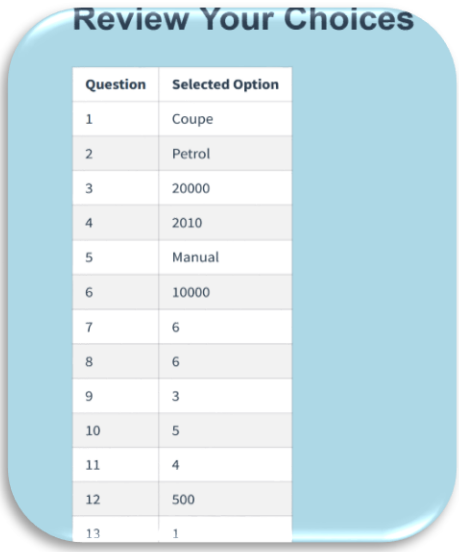

Figure 12: The selected choices are displayed to the user

Restarting the System with "Start Over"

- On the review page, users are also provided with a **"Start Over" button**, which allows them to clear all inputs and restart the entire selection process from scratch.
- This option gives users the flexibility to refine their choices if needed or explore different combinations to find the most suitable car.

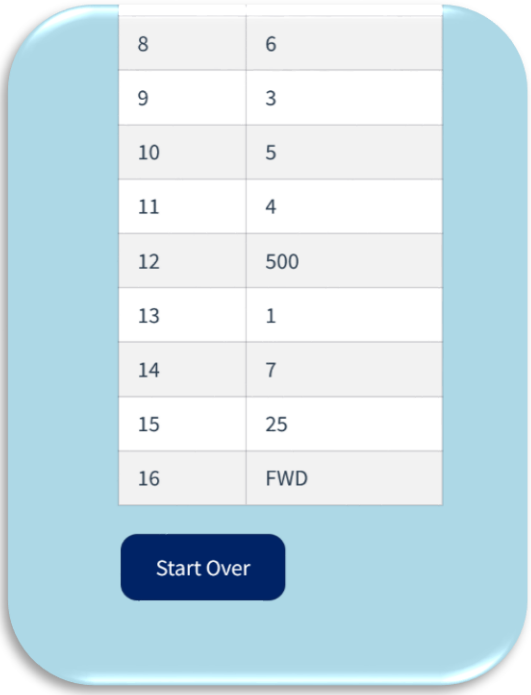

Figure 13: The user can select 'Start Over' and try again from the beginning

3.4 The Dataset

- A high-quality dataset is the backbone of any reliable AI model.
- For a car recommendation system to make accurate and meaningful predictions, the data it learns from must be comprehensive, clean, and well-prepared.
- Thorough research was done about user preferences and car features that make a significant difference to an individual car.
- Web scraping was done using BeautifulSoap (a python library) to gather car data and study car features and corresponding user preferences **[6]**.
- Based on the above, a custom Python script was written to generate a dataset with 10,000 unique records and 18 field attributes to represent the features of a specific car.

Figure 14: Image representing the Dataset

Dataset schema and description of the car attributes

- **Car ID**: A unique identifier for each car record.
- **Car Name**: The make and model of the car.
- **Body Type**: Represents the type of car, such as Sedan, SUV, Hatchback, etc.
- **Engine Type**: Specifies the type of engine used in the car, such as Petrol, Diesel, Electric, or Hybrid.
- **Price ($)**: The cost of the car, in USD, to help users filter based on their budget.
- **Year of Manufacture**: Indicates the manufacturing year, providing insights into the car's age and model year.
- **Transmission Type**: Specifies whether the car has an automatic or manual transmission.
- **Resale Value ($)**: Indicates the estimated resale value of the car, a key factor for users interested in long-term investment.

Car ID	Car	Body Type	Engine Typ	Price ($)	Year of Mar	Transmissi	Resale Valu
1	Mercedes (	Sedan	Petrol	164759.8	2022	Automatic	146327.2

Table 1: Dataset schema showing the car's features as field attributes

- **Fuel Economy (km/l)**: Measures the fuel efficiency of the car, often a top priority for cost-conscious buyers.

- **Performance Rating**: A score reflecting the car's engine power, acceleration, and overall driving experience.
- **User Rating**: A rating based on customer reviews, providing an aggregated score from user experiences.
- **Safety Rating**: Indicates the safety features and crash-test ratings of the car.
- **Comfort Level**: Reflects the car's interior quality, seating comfort, and ride smoothness.
- **Maintenance Cost ($/yr)**: Annual maintenance costs, helping users estimate ongoing expenses.
- **Warranty Period (years)**: The number of years covered under the manufacturer's warranty.
- **Seating Capacity**: The number of seats available, catering to users looking for specific passenger capacities.
- **Battery Capacity (kWh)**: Relevant for electric and hybrid cars, indicating the energy storage capacity of the vehicle's battery.
- **Drive Type**: Specifies the type of drivetrain, such as Rear-Wheel Drive (RWD), Front-Wheel Drive (FWD) or All-Wheel Drive (AWD).

Fuel Econo	Performan	User Rating	Safety Rati	Comfort Le	Maintenan	Warranty P	Seating Ca	Battery Cap	Drive Type
10.8	9	5	9	9	6778.7	2	5		RWD

Table 2: Dataset schema showing the car's features as field attribute

Dataset cleaning and preparation

- The raw dataset available now was structured and specific, but still could not be used to train the model.
- It had both numerical and categorical data.
- The dataset had string values (which cannot be sent as input to a node of the neural network), missing fields, outlier values, duplicate values and spiked values.
- The dataset had to be cleaned, normalized and the categorical string values had to converted to numerical representations before passing them as input to train a neural network.
- A custom python script was developed for this to clean, normalize and prepare the raw data.

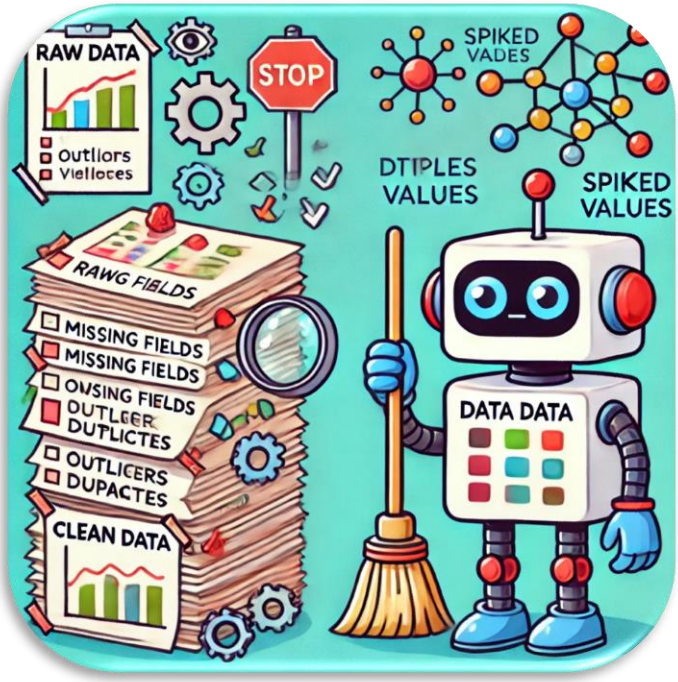

Figure 15: Image representing data cleaning and preparation

Essential python libraries to perform the Data cleaning and preparation

- **pandas (imported as pd) library** was used for data manipulation and analysis. It provided powerful data structures like DataFrames to store and process datasets.
- **MinMaxScaler** and **OneHotEncoder** are classes from the **scikit-learn** library, which helped with data normalization and converting categorical values into a machine-readable format.

```
import pandas as pd
from sklearn.preprocessing import MinMaxScaler, OneHotEncoder
```

Figure 16: code snippet 1 – library imports for data cleaning and preparation

MinMaxScaler: This function helps adjust numbers, so they fall within a certain range, typically between 0 and 1. By scaling all numbers based on the smallest and largest values, it makes sure that no single feature has an outsized impact on the model. This way, all features are on a similar scale, helping the model learn from the data more effectively **[6,9]**.

OneHotEncoder: This function turns categories (like "Sedan," "SUV," or "Hatchback") into a format the model can easily understand. Instead of just assigning each category a number, it creates a separate column for each category, marking a “1” in the column that matches the category and “0” in the others. This keeps all categories equal in the model’s eyes and avoids any unintended ranking or order **[9,6]**.

Normalizing Numerical Data

- The numerical columns where normalized using **Min-Max Scaling**. This scaled all values between 0 and 1 using the formula:

$$\text{Normalized Value} = \frac{(X - X_{\min})}{(X_{\max} - X_{\min})}$$

  - X = Original value
  - $X_{\min}$ = Minimum value in the dataset for the feature
  - $X_{\max}$ = Maximum value in the dataset for the feature

- This transformation ensures that all numerical features have a consistent scale, preventing larger values from disproportionately affecting the model **[6]**.

```
scaler = MinMaxScaler()
df[numerical_columns] = scaler.fit_transform(df[numerical_columns])
```

Figure 17: code snippet 2 – normalizing numerical data

Handling Missing Data

- Missing data can lead to skewed results and inaccurate predictions, making it essential to address these gaps.
- For categorical columns, missing values were replaced with the most frequent value (or mode). The mode represents the most common category within each column, helping to maintain the column's natural distribution **[6]**.

```
for col in categorical_columns:
    df[col] = df[col].fillna(df[col].mode()[0])
```

Figure 18: code snippet 3 – handling missing data

- Missing numerical values (e.g., price or performance ratings) were filled using the average value of the available data. This method keeps the dataset balanced without biasing towards any entry **[9]**.

$$N_{\text{filled}} = \frac{\sum_{i=1}^{n} N_i}{n}$$

- N_{filled} is the value used to fill missing entries.
- N_i represents each individual value in the dataset for the feature with missing values.
- n is the total number of non-missing entries for that feature.

Removing Duplicate Entries

- Duplicate records were removed from the dataset. Duplicate entries can distort model training, so it's essential to eliminate them to maintain data quality.

```
df = df.drop_duplicates()
```

Figure 19: code snippet 4 – removing duplicate entries

One-Hot Encoding for Categorical Variables

- The above code applies **One-Hot Encoding** to convert categorical values into binary (0 or 1) representations. For example, if a column 'Engine Type' had values 'Petrol', 'Diesel', and 'Electric', it is transformed into separate columns like 'Engine Type_Petrol', 'Engine Type_Diesel', and 'Engine Type_Electric', with 1 indicating presence and 0 indicating absence.

```
encoder = OneHotEncoder(sparse_output=False, handle_unknown='ignore')
encoded_columns = encoder.fit_transform(df[categorical_columns])
df_encoded = pd.DataFrame(encoded_columns, columns=encoder.get_feature_names_out(categori
```

Figure 20: code snippet 5 – one hot encoding for categorical values

- The fully cleaned and prepared dataset was saved in a new csv file which was sent as input the neural network model.

3.5 Neural Network Model

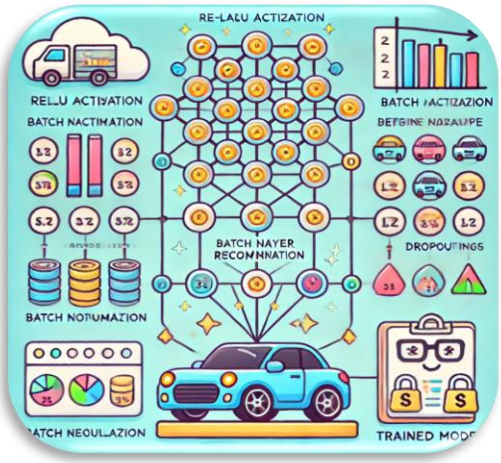

Figure 21: Image representing a Neural Network Model

Core Machine learning Concepts used in the model

ReLU (Rectified Linear Unit): This is a function used to help the neural network learn from data by allowing it to understand patterns and complex relationships. It works by letting the model focus only on positive values, making learning faster and helping it detect non-linear relationships, like those found in real-world data **[5,8]**.

Overfitting: Overfitting happens when the model learns too much from the training data, remembering it too closely rather than understanding general patterns. This makes it perform well on the training data but poorly on new, unseen data. Techniques like Dropout (temporarily ignoring some parts of the data) help the model avoid this problem by learning to generalize better **[5]**.

L2 Regularization: This is a technique that gently "penalizes" the model when it starts to rely too heavily on certain features. By adding a small adjustment, L2 Regularization keeps the model balanced, preventing it from focusing too much on specific data points and making it more adaptable **[10]**.

Softmax: Softmax is a function used in the output layer to help the model decide which category (or car type) is the best match for the input data. It assigns a probability to each option, showing how likely each car type is to be the best recommendation for the user, based on their preferences **[5]**.

RMSprop: RMSprop is a method that helps the model learn efficiently by adjusting how much it changes each time it learns from data. It makes learning smoother and more stable, helping the model reach a good performance without jumping around too much during training **[11]**.

Model Overview

- The neural network model for car recommendations processes 28 key features like price, engine type, and ratings to suggest the best car for users.
- It uses a multi-layer architecture where each layer identifies complex relationships between features.
- Key techniques include **ReLU activation** for non-linear learning, **Batch Normalization** to stabilize training, and **Dropout** to prevent overfitting.
- Data scaling ensures all features are treated fairly, while **L2 Regularization** prevents the model from relying too heavily on specific attributes.
- The output layer uses **Softmax** to assign probabilities to each car category. The model is trained using **Cross-Validation** for reliable performance and is optimized using **RMSprop**.
- It measures accuracy through metrics like precision and recall, ensuring the model learns effectively without memorizing data. Once trained, the model is saved for future predictions, offering personalized car recommendations based on user preferences **[9]**.

Library Imports:

- **pandas and NumPy:** Help manage and analyze large datasets efficiently.
- **scikit-learn functions**: Provide tools to split datasets, perform cross-validation, and scale data.
- **Keras functions**: Used to define and train deep learning models with layers, optimizers, and loss functions **[2]**.
- **Matplotlib** and **Seaborn**: Create visualizations to help understand and interpret the training process and results.

```
import pandas as pd
import numpy as np
from sklearn.model_selection import StratifiedKFold, train_test_split
from sklearn.preprocessing import MinMaxScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, Input, BatchNormalization
from tensorflow.keras.optimizers import RMSprop
from tensorflow.keras.initializers import HeNormal
from tensorflow.keras.regularizers import l2
from tensorflow.keras.losses import CategoricalCrossentropy
from tensorflow.keras.callbacks import EarlyStopping, ReduceLROnPlateau
from sklearn.metrics import classification_report, confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns
```

Figure 22: Code snippet 6 – library imports for Tensorflow deep learning model

Defining Features and Target Variables

- **X** contains the columns that represent characteristics of each car, such as price, ratings, fuel efficiency, etc. The code checks to ensure there are exactly 28 columns, which means each car is being described with 28 unique pieces of information.
- **Y** is the target variable (in this case, the specific car being recommended). By one-hot encoding, the car names are transformed into a format the model can understand. Each car is represented as a unique vector (e.g., [0, 1, 0] for Car B in a group of three cars).

```
# Define the feature set (X) explicitly with the list of 28 columns
X = df_final[[
    'Price ($)', 'Year of Manufacture', 'Resale Value ($)', 'Fuel Economy (km/l)',
    'Performance Rating', 'User Rating', 'Safety Rating', 'Comfort Level',
    'Maintenance Cost ($/yr)', 'Warranty Period (years)', 'Seating Capacity',
    'Battery Capacity (kWh)', 'Body Type_Convertible', 'Body Type_Coupe',
    'Body Type_Hatchback', 'Body Type_Minivan', 'Body Type_SUV', 'Body Type_Sedan',
    'Body Type_Wagon', 'Engine Type_Diesel', 'Engine Type_Electric',
    'Engine Type_Hybrid', 'Engine Type_Petrol', 'Transmission Type_Automatic',
    'Transmission Type_Manual', 'Drive Type_AWD', 'Drive Type_FWD',
    'Drive Type_RWD'
]]

# Confirm that the number of features matches the expectation
assert X.shape[1] == 28, f"Expected 28 features, but found {X.shape[1]}"

# One-hot encode the target variable (car names)
= pd.get_dummies(df_final['Car'])
```

Figure 23: Code snippet 7 – defining features and target variables

Cross-Validation and Callbacks

- **Cross-Validation (Stratified K-Fold)** divides the dataset into five parts (or "folds") to validate the model's performance consistently. It ensures that each fold has a similar mix of different car categories, providing more reliable results **[1,3]**.
- **Early Stopping** is like setting an alarm to stop training if no improvement is detected in the model's performance (measured by validation loss). This prevents the model from training endlessly and overfitting the data **[8,11]**.
- **Learning Rate Scheduler**: If the model's performance doesn't improve for a few rounds (epochs), this scheduler automatically reduces the speed (learning rate) at which the model learns, giving it more time to refine its learning **[5]**.

```
skf = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
early_stopping = EarlyStopping(monitor='val_loss', patience=8, restore_best_weights=True)
lr_scheduler = ReduceLROnPlateau(monitor='val_loss', factor=0.5, patience=4, min_lr=1e-6)
```

Figure 24: Code snippet 8 – cross validation and callbacks

Cross-Validation Loop

- This loop repeats the training process five times (one for each fold). Each time, the dataset is split into training data and validation data.

- **Training Data** is what the model learns from.
- **Validation Data** is a smaller set that helps measure how well the model is doing after each round of training. It's like holding back some test questions to check if the student (model) is learning correctly **[7]**.

```
for fold, (train_index, val_index) in enumerate(skf.split(X_scaled, Y.values.argmax(1))):
    print(f"--- Fold {fold + 1} ---")
    X_train, X_val = X_scaled[train_index], X_scaled[val_index]
    Y_train, Y_val = Y.iloc[train_index], Y.iloc[val_index]
```

Figure 25: Code snippet 9 – cross validation loop

The Neural Network

- **It is a Sequential Model,** meaning the layers are stacked in order, from input to output.
- **Input Layer**: Takes 28 features (like engine type, safety rating, etc.).
- **First Hidden Layer**: Contains 256 neurons, which process these features. Each neuron is a small decision-maker that looks at different parts of the car data.
- **ReLU Activation** helps the model capture more complex relationships between features.
- **HeNormal Initialization** sets the initial weights in a way that accelerates training.
- **L2 Regularization** applies a penalty to the size of the weights, preventing overfitting.
- **Batch Normalization** standardizes the output of this layer to improve training stability.
- **Dropout** randomly "turns off" half the neurons during training, preventing the model from becoming too reliant on specific neurons (which reduces overfitting).

```
model = Sequential()
model.add(Input(shape=(28,)))  # Input Layer with 28 features

model.add(Dense(256, activation='relu', kernel_initializer=HeNormal(), kernel_regularizer=l2
model.add(BatchNormalization())
model.add(Dropout(0.5))
```

Figure 26: Code snippet 10 – Neural Network model initialization

Additional Hidden layers

- The model has additional hidden layers with progressively fewer neurons (128 and 64), each learning smaller details and features from the car data.

- The reduced neuron count helps the model refine its learning step-by-step. By gradually narrowing down options when deciding, these layers allow the model to focus on the most relevant features **[7]**.
- Dropout rates (40% and 30%) gradually decrease to help the model stabilize its learning.

```
model.add(Dense(128, activation='relu', kernel_initializer=HeNormal(), kernel_regularizer=l
model.add(BatchNormalization())
model.add(Dropout(0.4))

model.add(Dense(64, activation='relu', kernel_initializer=HeNormal(), kernel_regularizer=l2(
model.add(BatchNormalization())
model.add(Dropout(0.3))
```

Figure 27: Code snippet 11 – Additional Hidden Layers

Output Layer

- The final layer uses a **Softmax Activation** function, which converts the model's output into probabilities for each car category. For example, if there are 10 different cars, Softmax assigns a probability to each one, indicating how confident the model is about each choice **[7]**.

```
model.add(Dense(Y_train.shape[1], activation='softmax'))
```

Figure 28: Code snippet 12 – Output layer

Compiling the Model

- **Compiling** is like setting the rules and strategy for training the model.
- **Optimizer (RMSprop)** adjusts the model's weights to minimize errors.
- **Loss Function (Categorical Cross-Entropy)** measures the difference between the predicted and actual car categories. It tells the model how far off it is from the correct answer.
- **Accuracy Metric** calculates how often the model's predictions match the actual car categories.

```
model.compile(optimizer=RMSprop(learning_rate=0.0005),
              loss=CategoricalCrossentropy(),
              metrics=['accuracy'])
```

Figure 29: Code snippet 13 – Compiling the model

Training the model

- **Model Fit**: This command starts the training process, where the model learns from the training data.
- **Validation Data**: The model checks its progress against validation data to see how well it's learning.
- **Epochs**: Represents the number of times the entire dataset is processed. Each pass (epoch) helps the model learn a little better **[10]**.
- **Batch Size**: Determines how many samples the model processes at once. In this case, the model handles 64 samples at a time to optimize memory and speed.

```
history = model.fit(X_train, Y_train,
                    validation_data=(X_val, Y_val),
                    epochs=100,
                    batch_size=64,
                    verbose=1,
                    callbacks=[early_stopping, lr_scheduler])
```

Figure 30: Code snippet 14 – Training the model

Evaluating Each Fold

- After each round of training, the model was tested on the validation data to measure how well it learned. This line prints the percentage of correct predictions (validation accuracy) for each fold.
- A total of 5 folds were created, with data visualization mat plots drawn and displayed to thoroughly analyze the accuracy of training for the fold **[11]**.

```
val_loss, val_accuracy = model.evaluate(X_val, Y_val, verbose=0)
print(f"Fold {fold + 1} Validation Accuracy: {val_accuracy * 100:.2f}%")
```

Figure 31: Code snippet 15 – Evaluating Each Fold

Final Model Split and Creation

- The entire dataset was split into a larger **training set** (X_train_full, Y_train_full) and a smaller **test set** (X_test, Y_test). The test set was kept separate for evaluating the final performance of the trained model.

- After defining the new training and test sets, a final model was built using the same layers and parameters as in the cross-validation loop. This ensures consistency in model design and allows the final model to leverage the complete dataset for training, except for the set-aside test data **[2]**.

```
_train_full, X_test, Y_train_full, Y_test = train_test_split(X_scaled, Y, test_size=0.15,

final_model = Sequential()
final_model.add(Input(shape=(28,)))  # Input Layer with 28 features
# Hidden Layers similar to previous
final_model.add(Dense(256, activation='relu', kernel_initializer=HeNormal(), kernel_regular
final_model.add(BatchNormalization())
final_model.add(Dropout(0.5))
final_model.add(Dense(128, activation='relu', kernel_initializer=HeNormal(), kernel_regular
final_model.add(BatchNormalization())
final_model.add(Dropout(0.4))
final_model.add(Dense(64, activation='relu', kernel_initializer=HeNormal(), kernel_regulari
final_model.add(BatchNormalization())
final_model.add(Dropout(0.3))
nal_model.add(Dense(Y_train_full.shape[1], activation='softmax'))
```

Figure 32: Code snippet 16 – Final Model Split and Creation

Training of the Final Model

- The final model was now trained on the complete training set (X_train_full, Y_train_full). The same parameters (100 epochs, batch size of 64) and callbacks (early stopping and learning rate reduction) were applied to maintain the model's performance and prevent overfitting **[2]**.

```
history_final = final_model.fit(X_train_full, Y_train_full,
                                epochs=100,
                                batch_size=64,
                                verbose=1,
                                callbacks=[early_stopping, lr_scheduler])
```

Figure 33: Code snippet 17 – Training of the final model

Saving the Final Model

- The final trained model was saved in the. keras format, allowing it to be reloaded and used for predictions later. Saving the model also preserved all the weights and configurations, enabling further fine-tuning if needed.

```
final_model.save('fine_tuned_car_recommendation_model.keras')
```

Figure 34: Code snippet 18 – Saving the final model

4. Individual Contribution and meeting Unit Learning Outcomes

4.1 Contributions, Source code and GitHub Link

I, Arun Ragavendhar, played a major, most important and significant role in developing the AI Car Purchase Recommendation System.

- Lead Software Developer, Researcher, Machine Learning Engineer, Data Engineer
- Created datasets, designed and developed the Neural network model.
- Designed and Created the Streamlit Web application and integrated it with the model.
- Created Visualization plots and real-life user tests to test, debug and finetune the whole system

Git Hub Link

The complete source code is available in the above Git Hub Link.

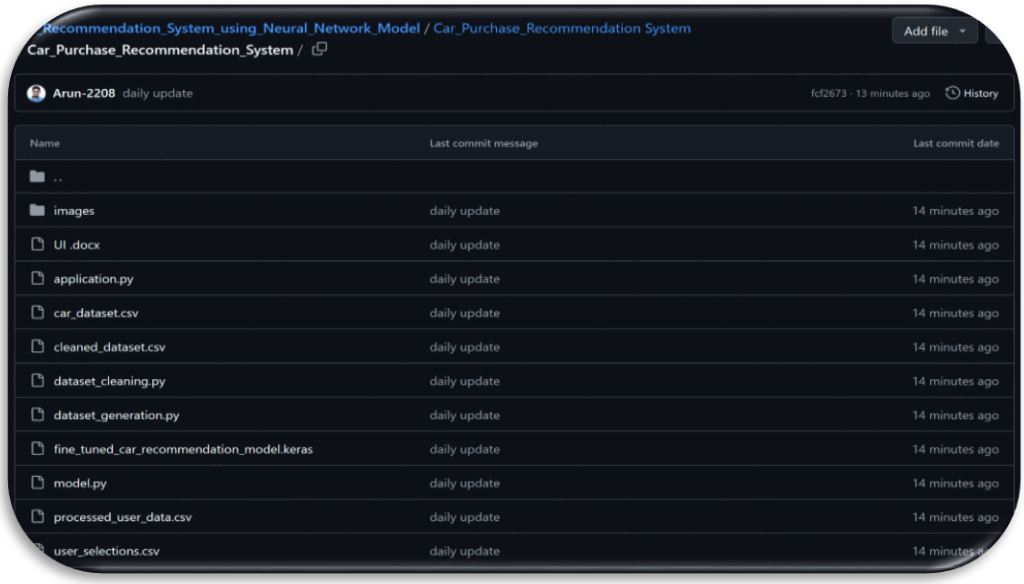

Figure 35: Screenshot of My GitHub page of the source code of the project

I have addressed each learning outcome with targeted actions and delivering a robust solution that bridges software engineering and data science skills.

4.2 Unit learning outcomes and How I met them – with examples

1. **Applying a Systematic Approach to Technology Design**
   A structured approach guided each phase, from data preparation to model development, testing, and final deployment, ensuring the project met its objectives effectively.

   - **Example 1**: I constructed a dataset of 10,000 records with 18 attributes—including key features like body type, engine type, and resale value—capturing diverse user preferences and providing a strong foundation for accurate model predictions. This dataset was meticulously cleaned and organized, reflecting the systematic planning essential for quality machine learning outcomes.
   - **Example 2**: The neural network model was designed with a layered approach: 256 neurons in the first hidden layer, progressively reducing in subsequent layers to optimize learning and prevent overfitting. ReLU activation, Batch Normalization, and Dropout layers (with rates of 40% and 30%) were applied, leading to a high-performing model capable of making nuanced recommendations.
   - **Example 3**: A "Start Over" button was integrated into the review page, allowing users to reset and re-enter their choices. This feature enhanced usability by providing flexibility, reflecting a structured approach to ensuring the application adapted to varied user journeys and preferences.

   One challenge encountered was ensuring data uniformity across all records, which was essential for achieving consistent model accuracy. Addressing these required multiple iterations of data cleaning, reinforcing the importance of a systematic approach in machine learning projects.

2. **Applying Knowledge of Design Fundamentals to Technology Challenges**
   Design principles were leveraged to address technical challenges and create an accessible, effective recommendation system.

   - **Example 1**: The neural network was implemented as a Multi-Layer Perceptron (MLP) using a sequential model in TensorFlow, applying L2 Regularization and HeNormal initialization to optimize training and improve generalization. This architectural design balanced accuracy and training efficiency, addressing the challenge of preventing overfitting.
   - **Example 2**: A user-friendly interface was developed in Streamlit with clickable image buttons instead of dropdowns, providing a more visually intuitive selection process for users. This design decision improved accessibility, allowing diverse users to interact with the system easily and enhancing overall engagement.
   - **Example 3**: Stratified K-Fold cross-validation was used to handle imbalanced data across categories, ensuring that each class was well-represented during

training. This approach boosted model accuracy in delivering personalized recommendations and highlighted the importance of designing adaptable systems for real-world data diversity.

3. **Finding, Organizing, and Evaluating Information on Technology Design**
   Extensive research and careful data organization supported the development of a comprehensive and effective recommendation model.

   - **Example 1**: Key car features—such as fuel economy, safety ratings, and user ratings—were identified through research as critical decision factors. This guided the dataset structure, ensuring it included 18 well-rounded attributes that reflected real-world user preferences, thus enhancing model relevance and accuracy.
   - **Example 2**: Web scraping using BeautifulSoup (a python library) gathered relevant car data from multiple online sources. These insights were studied deeply, and a custom python script was written to generate a dataset of 10,000 high-quality records with comprehensive attributes. This data collection step ensured the model's accuracy, providing real-world input for model training and producing results aligned with current user needs.
   - **Example 3**: Platforms like CarWow and Cars24 were reviewed to understand their limitations in personalization. Insights from these evaluations influenced my approach, leading to a more adaptable design that captured complex user preferences beyond simple filtering, positioning the model as a personalized alternative to existing systems.

   Collecting and filtering reliable car data through web scraping presented obstacles due to inconsistent data formats. Overcoming this challenge by writing a custom python script for data generation honed my skills in data preprocessing and reinforced the value of thorough data evaluation.

4. **Using Technology to Develop and Present Design Solutions**
   Multiple technologies were employed to build the recommendation model and the interactive user interface, creating an end-to-end solution that connected the neural network with a user-friendly front end.

   - **Example 1**: The MLP model was developed in TensorFlow with careful parameter tuning, including 100 training epochs and Early Stopping, to balance learning efficiency and model accuracy. This process resulted in a **90.86%** accuracy rate, demonstrating effective use of machine learning to solve the recommendation problem.
   - **Example 2**: An intuitive web interface was created in Streamlit, allowing users to input preferences through image-based buttons rather than traditional dropdowns. This layout provided a smooth and interactive experience, emphasizing usability and engagement, particularly for users with minimal technical backgrounds.

- **Example 3**: Personalized visual feedback was incorporated, displaying a recommendation message that reinforced user engagement and offered clear guidance based on inputs. This feature connected technical backend functions with an approachable front end, demonstrating the application's practical, user-centred design.

5. **Demonstrating Reflective Practice and Using Self and Peer Evaluation**
   Continuous self-reflection and responsiveness to feedback were key to enhancing design effectiveness and model performance.

   - **Example 1**: Early Stopping and learning rate scheduling were implemented based on tutor feedback, optimizing training and achieving a final model accuracy of 90.86%. This adjustment highlighted the importance of considering external input in model tuning to achieve the best results.

   - **Example 2**: Peer feedback suggested switching from dropdowns to clickable image buttons, leading to a more engaging and accessible interface. This adjustment, in response to user testing, demonstrated the value of iterative improvement based on real-world use cases and peer insights.

   - **Example 3**: Adjustments in data ordering for model inputs resolved initial mismatches, where user data did not fully align with model requirements. By addressing this issue, I improved prediction accuracy, reflecting on and refining each project component to meet functional standards.

   Implementing feedback from our tutor, such as switching from dropdowns to clickable image buttons, significantly improved the interface. This process highlighted how collaborative feedback can enhance usability and project effectiveness.

6. **Demonstrating Awareness of Social and Cultural Perspectives in Team Work**
   The design of the system considered inclusivity and user diversity, ensuring relevance to varied social and cultural perspectives.

   - **Example 1**: User preferences, including budget constraints, eco-friendliness, and luxury features, were integrated to meet a diverse range of needs. These elements ensured the model could cater to users with differing priorities, from economic choices to high-end requirements.

   - **Example 2**: Team discussions fostered open input from all members, allowing each person to contribute ideas on inclusivity and design. This collaborative approach created an environment of respect and encouraged the development of a system that considered various perspectives.

   - **Example 3**: The application's simple, visually engaging design—featuring clear labels and images—was tailored to users of varying technological familiarity, enhancing accessibility. This choice demonstrated an understanding of user diversity, allowing the system to support users of all backgrounds effectively.

5. Reflections

5.1 Methods

Throughout the project, multiple methods were carefully applied, spanning data preparation, model training, and evaluation, each contributing to an improved understanding of machine learning fundamentals. With a background in software engineering, these methods were new to me and highlighted the distinctions between software development and data science, marking a significant shift in my learning process.

- **Data Cleaning and Preparation**: Early in the project, I understood the importance of transforming raw data into a high-quality format for machine learning. Techniques such as Min-Max Scaling and One-Hot Encoding were applied to standardize the 10,000-record dataset containing 18 attributes (e.g., body type, engine type, price, and user ratings). Min-Max Scaling ensured that numerical features like car prices, which could range widely, were scaled down between 0 and 1, preventing any one feature from disproportionately influencing the model. One-Hot Encoding transformed categorical features like engine type and car body style into binary format, which allowed the model to interpret each attribute effectively. By meticulously preparing data, I saw firsthand how a well-prepared dataset lays the foundation for reliable and accurate predictions.

- **Model Training Techniques**: When transitioning from theory to practical implementation, I applied Dropout and Batch Normalization, which were instrumental in controlling overfitting. Dropout rates of 40% in the first layer and 30% in subsequent layers were set to randomly ignore neurons during each training iteration, preventing the model from relying too heavily on specific nodes and improving its generalization to new data. Batch Normalization, applied in every layer, ensured that data passed to each layer maintained consistent distribution, allowing the model to train faster and more reliably. Testing various configurations taught me how small adjustments to training parameters can significantly impact model stability and performance, reinforcing the importance of fine-tuning neural networks for real-world applications.

- **Cross-Validation and Early Stopping**: Stratified K-Fold Cross-Validation was employed to evaluate model robustness across different data samples, dividing the dataset into five distinct folds and training on different combinations. This method ensured balanced representation of each class across folds, reinforcing model consistency. Early Stopping further optimized training by halting the process when validation accuracy reached a stable point, reducing the risk of overfitting. Together, these techniques helped the model achieve a high accuracy of 90.86% while preventing excessive training cycles, showing me the value of balancing training efficiency with high model reliability.

- **Personal Impact and Real-World Application:** Learning these methods provided unexpected insights beyond just technical skills. Given my software engineering background, this project's dive into data science and machine learning was both challenging and enriching. Initially, methods like Dropout and Batch Normalization felt complex; however, mastering

them has equipped me with a problem-solving mindset applicable beyond this project. For instance, I now feel more confident tackling any data-intensive tasks, knowing that a systematic approach to data preparation and model tuning is critical to achieving reliable results. Working with data preparation and model tuning highlighted the importance of systematic handling of datasets. This experience has prepared me for future roles in AI, where data quality and model reliability are critical for success.

5.2 Technical Learning

Starting from a pure software engineering background, this project offered a transformative learning experience, exposing me to essential machine learning concepts, data engineering techniques, and user-centred design. Each phase, from data preparation to model development and web application creation, strengthened my practical skills and broadened my understanding of how software engineering and data science intersect.

- **TensorFlow for Neural Networks**: Constructing a Multi-Layer Perceptron (MLP) model in TensorFlow required an understanding of each architectural component and its impact on model behaviour. The model was designed with 18 input features, including user-centric attributes like fuel economy, safety ratings, and car type, and comprised three hidden layers with neuron counts progressively decreasing from 256 to 128 to 64. Activation functions like ReLU were used to introduce non-linearity, while L2 Regularization mitigated overfitting by penalizing large weights. By iterating through configurations, testing Dropout and Batch Normalization settings, I saw how the interaction of each element affected model performance. This practical experience with TensorFlow equipped me with foundational skills in neural network design, moving neural networks from a theoretical concept to an applied skill I can now confidently use.

- **Future Preparedness and Learning Growth:** The experience of learning TensorFlow was transformative and solidified my goals moving forward. Learning TensorFlow and building a neural network from scratch has not only broadened my technical skills but has also shown me how to apply these concepts in real-world scenarios in future works. This hands-on experience prepared me to design adaptable AI solutions and refine my approach to user-centred design. Looking forward, I aim to deepen my expertise in AI, with a specific focus on creating user-friendly applications that integrate seamlessly with complex backend models. This hands-on experience with TensorFlow has equipped me to design adaptable AI solutions in the future. Building an interactive application has also strengthened my understanding of how to connect complex models to user-friendly interfaces, which is crucial for future projects where usability and functionality must align.

- **Streamlit for Interactive Web Applications**: Building a front-end interface in Streamlit introduced me to the seamless integration of machine learning models with web applications. I developed an interactive layout where users could select car preferences through clickable image buttons rather than dropdowns, ensuring ease of use and visual appeal. Designing this visually intuitive interface with four structured pages and 16 questions improved user engagement and accessibility, reinforcing the practical value of user-centred

design in applications. Working with Streamlit bridged my software engineering skills with machine learning, demonstrating how to present complex backend functionality in a clear, interactive format accessible to a non-technical audience.

- **Data Engineering**: Handling data preparation and cleaning was essential for effective machine learning, and I gained valuable skills in this area. Techniques like data normalization and handling missing data prepared the dataset to deliver consistent, high-quality inputs for the model. By ensuring that the dataset of 10,000 car records was clean, well-scaled, and representative of varied user needs, I created a dataset that was essential to the model's reliability. This hands-on experience taught me the importance of data engineering as a foundation for machine learning, enhancing my ability to manage data effectively in any project.

This project has not only equipped me with new technical skills but also given me confidence in applying data science methods to practical challenges. I began from the basics, learning about data collection, preprocessing, and model design, gradually building on this knowledge to create an effective recommendation system. Moving forward, I aim to deepen my understanding of machine learning, including exploring advanced neural network architectures and further improving my skills in creating interactive applications that bring machine learning insights directly to users.

5.3 Challenges and issues Faced and how it was fixed

Addressing Overfitting During Model Training

Issue

- During the training phase, the neural network model initially showed signs of overfitting. Overfitting occurs when the model becomes overly tailored to the training data, resulting in excellent performance on known data but poor accuracy on new, unseen data.
- This issue was identified when the training accuracy remained consistently high while the validation accuracy either plateaued or showed a declining trend.

Resolution

- To address this problem, Dropout layers were incorporated into the neural network. Dropout works by randomly deactivating a proportion of neurons during each training iteration, preventing the model from overly relying on specific neurons.
- Additionally, L2 Regularization was applied to add a slight penalty to larger weights, encouraging the model to distribute its attention more evenly across all features.
- These techniques collectively improved the model's ability to generalize, thereby enhancing its performance on validation datasets as well as new datasets.

Evaluating Model Performance and Accuracy

Issue

- Accurately assessing the model's performance presented a unique challenge, especially in dealing with imbalanced classes and multiple car categories.
- At first, there was a risk that the model would favor more common car categories while struggling to correctly predict less frequent ones, thereby compromising its overall effectiveness.

Resolution

- To address this challenge, the technique of **Stratified K-Fold Cross-Validation** was implemented. This approach divides the data into multiple folds, ensuring that each fold maintains a balanced distribution of all car categories.
- This method provided a more reliable and comprehensive evaluation of the model's capabilities. Furthermore, a range of performance metrics was utilized, including **Precision** (indicating the percentage of correct predictions for each car type), **Recall** (measuring how well the model identified actual car types), and **F1-Score** (which balances precision and recall).
- These metrics offered a detailed assessment of the model's classification performance across all categories, ensuring that both common and less frequent car types were accurately represented.

Ensuring Correct Data Ordering for Model Input

Issue

- One critical challenge encountered during development was ensuring that the cleaned data had its features in the exact order required by the neural network model. The model expected the input features—such as normalized numerical values (like price or ratings) and one-hot encoded categorical values (like body type or engine type)—to be arranged in a specific sequence. However, the questions in the web application were initially collected in a different order, leading to a mismatch between the way the model expected data and the actual order of the collected inputs.
- This mismatch resulted in the wrong values being fed into the wrong fields within the model. For example, the feature meant to represent "body type" was being fed into a field representing "engine type," which initially led to distorted predictions and reduced model accuracy.

Resolution

- The solution involved rearranging the questions in the application to match the exact order required by the neural network. After collecting user responses, an additional step was introduced to reorder the collected data to precisely align with the model's expected feature

sequence. This involved creating a mapping that linked each collected user input to the appropriate feature column. By performing these checks and reordering steps, the issue of feeding incorrect data into the model's fields was resolved, ensuring that each feature aligned perfectly with the model's structure and produced accurate predictions.

5.4 Improvements made on feedback received

The project underwent two major improvements based on feedback and suggestions given

by our tutor **Dr. Xinyi Cai.**

Early Stopping and Epoch Reduction

- The training process initially ran for an excessive number of epochs (175), leading to unnecessary computation and potential overfitting.
- Based on feedback, the number of epochs was reduced (100), and an **Early Stopping** mechanism was introduced to automatically halt training once the model's loss stabilized.
- This optimization reduced computation time and improved model efficiency.

UI Enhancement with Clickable Buttons

- Initially, the app relied on dropdowns and sliders, which were functional but lacked visual appeal. Based on feedback to make the app more engaging, the design was updated to include clickable image-based buttons.
- This change not only improved interactivity but also provided a more interactive and dynamic experience for users.

6. Project Outcomes

6.1 Product testing, usage results and plots

Data set Cleaning and Processing

The raw data (Table 3) contained essential car attributes, including model, body type, engine type, price, and ratings, but it required significant processing to be model-ready.

Car ID	Car	Body Type	Engine Type	Price ($)	Year of Man	Transmissi	Resale Valu	Fuel Econo	Performanc	User Rating	Safety Ratir	Comfort Le	Maintenanc	Warranty P	Seating Ca	Battery Cap	Drive Type
1	Mercedes C	Sedan	Petrol	164759.8	2022	Automatic	146327.2	10.8	9	5	9	9	6778.7	2	5		RWD
2	Hyundai Ko	Sedan	Petrol	35700.73	2022	Manual	24067.08	18.5	6	8	8	7	2650.22	2	4		FWD
3	Chevrolet C	Sedan	Diesel	77119.21	2013	Automatic	56006.11	11.1	10	10	8	5	2546.06	3	2		AWD
4	Porsche 91	SUV	Hybrid	177262.1	2024	Automatic	132843.4	9.4	8	8	10	10	6876.48	1	4		AWD
5	Jaguar F-Pa	SUV	Petrol	185014.6	2024	Automatic	150085.1	8.8	10	5	9	9	6007.27	3	5		AWD
6	Chevrolet C	Convertible	Diesel	81984.28	2016	Automatic	55428.76	10.1	10	9	6	5	3191.86	5	4		AWD
7	BMW 7 Seri	Coupe	Diesel	171645.4	2021	Automatic	120240.2	9	8	9	10	8	6605.04	2	4		AWD
8	Mercedes S	SUV	Diesel	177515.6	2016	Automatic	129073.6	11.8	9	9	10	10	4020.6	1	4		AWD
9	Kia Niro EV	Hatchback	Hybrid	51193.95	2015	Automatic	37188.83	25.5	6	7	8	8	813.21	3	5		FWD
10	Hyundai Ior	Hatchback	Electric	53745.96	2021	Automatic	42282.92	25.2	6	10	7	7	1424.08	2	5	68	FWD

Table 3: Raw data

Hence, a custom python script was written to clean and prepare the raw dataset.

The final cleaned dataset (Table 4) contained 28 structured features across 10,000 records, optimized for training the MLP neural network, all of them having data in the specific numerical form as required by the model.

This refined dataset provided a consistent and balanced input, improving the model's learning capacity and reliability.

Price ($)	Year of Mai	Resale Val	Fuel Econo	Performan	User Rating	Safety Rati	Comfort Le	Maintenan	Warranty P	Seating Ca	Battery Ca	Body Type_	Body Type_	Body Type_	Body Type_	Body Type_	Body Type_	Body Type_	Engine Typ	Engine Typ	Engine Typ	Engine Typ	Transmissi	Transmissi	Drive Type_	Drive Type_	Drive Type_	Car	Car_ID
0.809793	0.857143	0.81	0.127273	0.833333	0	0.833333	0.833333	0.968147	0.25	0.6	0.474343	0	0	0	0	0	1	0	0	0	0	1	1	0	0	1	Mercedes (	1
0.111866	0.857143	0.103102	0.477273	0.333333	0.6	0.666667	0.5	0.331528	0.25	0.4	0.474343	0	0	0	0	0	1	0	0	0	0	1	0	1	0	1	0	Hyundai Ko	2
0.335849	0.214286	0.28777	0.140909	1	1	0.666667	0.166667	0.315466	0.5	0	0.474343	0	0	0	0	0	1	0	1	0	0	0	1	0	1	0	0	Chevrolet (	3
0.877403	1	0.732038	0.063636	0.666667	0.6	1	1	0.983224	0	0.4	0.474343	0	0	0	0	1	0	0	0	0	1	0	1	0	1	0	0	Porsche 91	4
0.919327	1	0.831728	0.036364	1	0	0.833333	0.833333	0.849191	0.5	0.6	0.474343	0	0	0	0	1	0	0	0	0	0	1	1	0	1	0	0	Jaguar F-Pa	5
0.362159	0.428571	0.284432	0.095455	1	0.8	0.333333	0.166667	0.415049	1	0.4	0.474343	1	0	0	0	0	0	0	1	0	0	0	1	0	1	0	0	Chevrolet (	6
0.847029	0.785714	0.659167	0.045455	0.666667	0.8	1	0.666667	0.941368	0.25	0.4	0.474343	0	1	0	0	0	0	0	1	0	0	0	1	0	1	0	0	BMW 7 Seri	7
0.878773	0.428571	0.710241	0.172727	0.833333	0.8	1	1	0.542843	0	0.4	0.474343	0	0	0	0	1	0	0	1	0	0	0	1	0	1	0	0	Mercedes S	8
0.195651	0.357143	0.17897	0.795455	0.333333	0.4	0.666667	0.666667	0.048257	0.5	0.6	0.474343	0	0	1	0	0	0	0	0	0	1	0	1	0	0	1	0	Kia Niro EV	9
0.209451	0.785714	0.208424	0.781818	0.333333	1	0.5	0.5	0.142455	0.75	0.6	0.600751	0	0	1	0	0	0	0	0	1	0	0	1	0	0	1	0	Hyundai Ior	10

Table 4: Cleaned, Proccessed and Prepared data

Trained Neural Network Accuracy

The neural network model was trained and evaluated using a 5-fold cross-validation process, where each fold involved training the model and tracking both accuracy and loss reduction. The following figures illustrate the performance across each fold:

- Figures 36 to 40 show the training accuracy and loss curves for each fold.
- Each plot reflects a steady reduction in loss and an increase in accuracy as the training progressed, demonstrating effective learning across all folds.
- This consistent performance indicates that the model generalized well without significant overfitting, thanks to techniques like Dropout and Batch Normalization.

Training accuracy and Fold loss reduction after completion of the training of the 1st fold of dataset

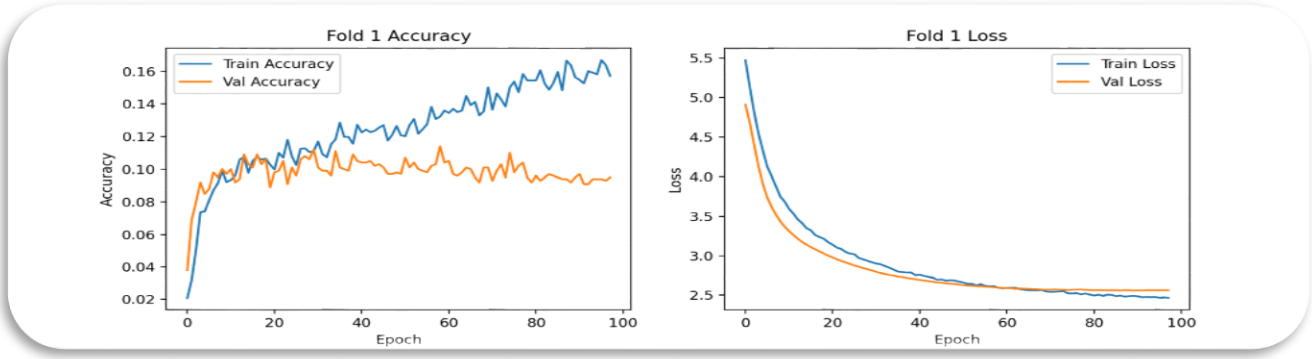

Figure 36: A mat plot of the training Accuracy and Loss curve of the 1st fold of the dataset

```
poch 96/100
63/63 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.1644 - loss: 2.4643 - val_accuracy: 0.0940 - val_loss: 2.5599 - lea
rning_rate: 1.2500e-04
Epoch 97/100
63/63 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.1767 - loss: 2.4495 - val_accuracy: 0.0930 - val_loss: 2.5604 - lea
rning_rate: 1.2500e-04
Epoch 98/100
63/63 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.1601 - loss: 2.4561 - val_accuracy: 0.0950 - val_loss: 2.5601 - lea
rning_rate: 1.2500e-04
Fold 1 Validation Accuracy: 91.20%
```

Figure 37: Epoch cycles and training accuracy value

Training accuracy and Fold loss reduction after completion of the training of the 2nd fold of dataset

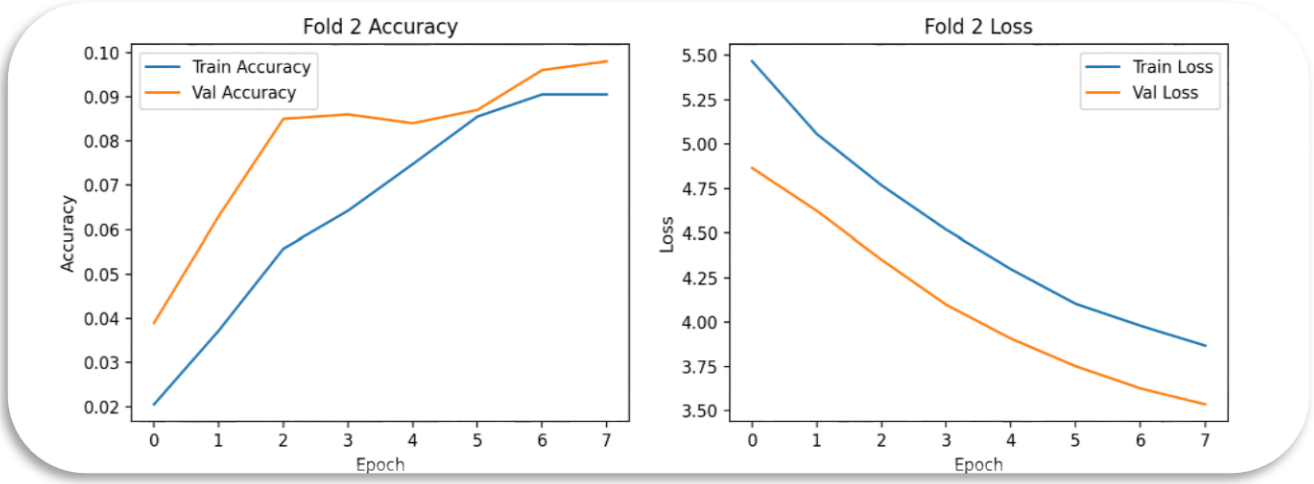

Figure 38: A mat plot of the training Accuracy and Loss curve of the 2nd fold of the dataset

Training accuracy and Fold loss reduction after completion of the training of the 3rd fold of dataset

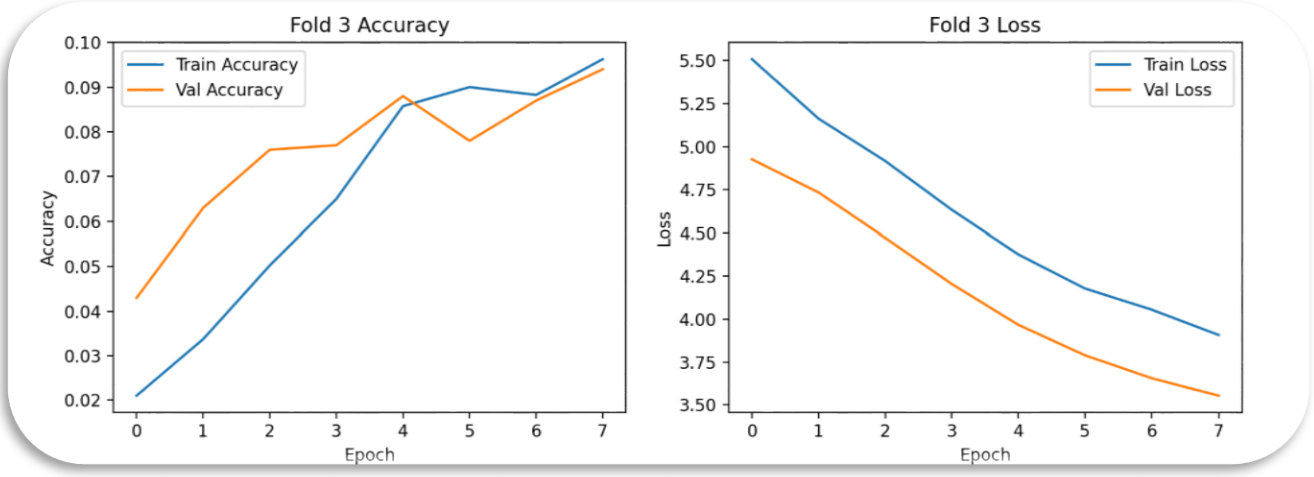

Figure 39: A mat plot of the training Accuracy and Loss curve of the 3rd fold of the dataset

Training accuracy and Fold loss reduction after completion of the training of the 4th fold of dataset

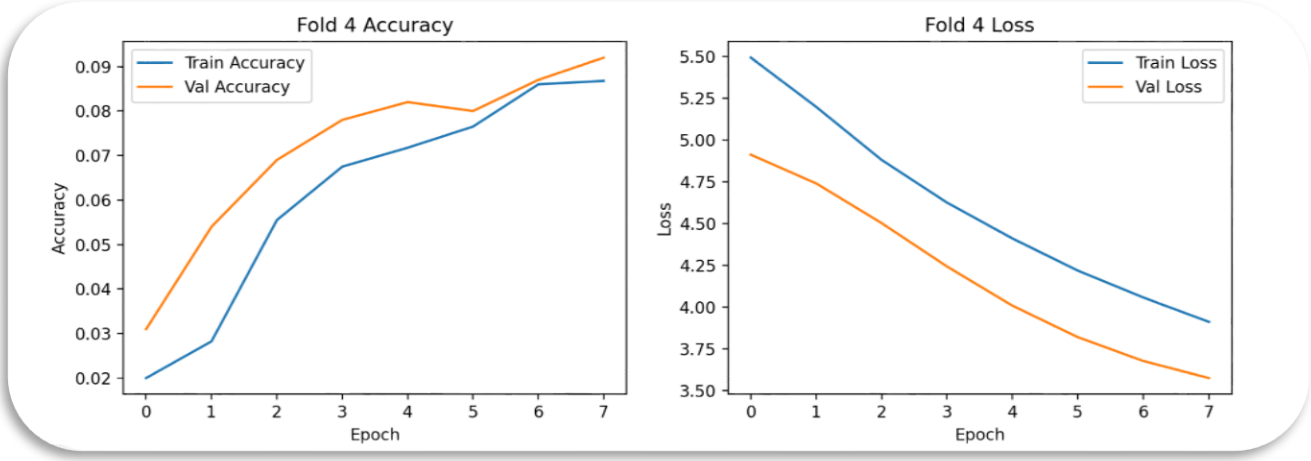

Figure 40: A mat plot of the training Accuracy and Loss curve of the 4th fold of the dataset

Training accuracy and Fold loss reduction after completion of the training of the 5th fold of dataset

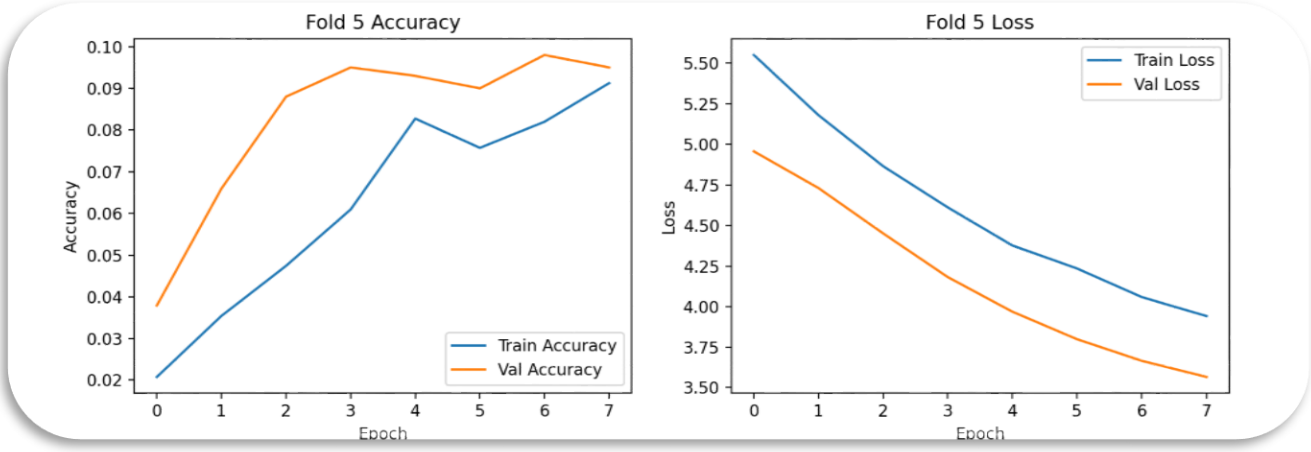

Figure 41: A mat plot of the training Accuracy and Loss curve of the 5th fold of the dataset

Trained Neural Network Accuracy

The neural network model achieved a final test accuracy of 90.86 %

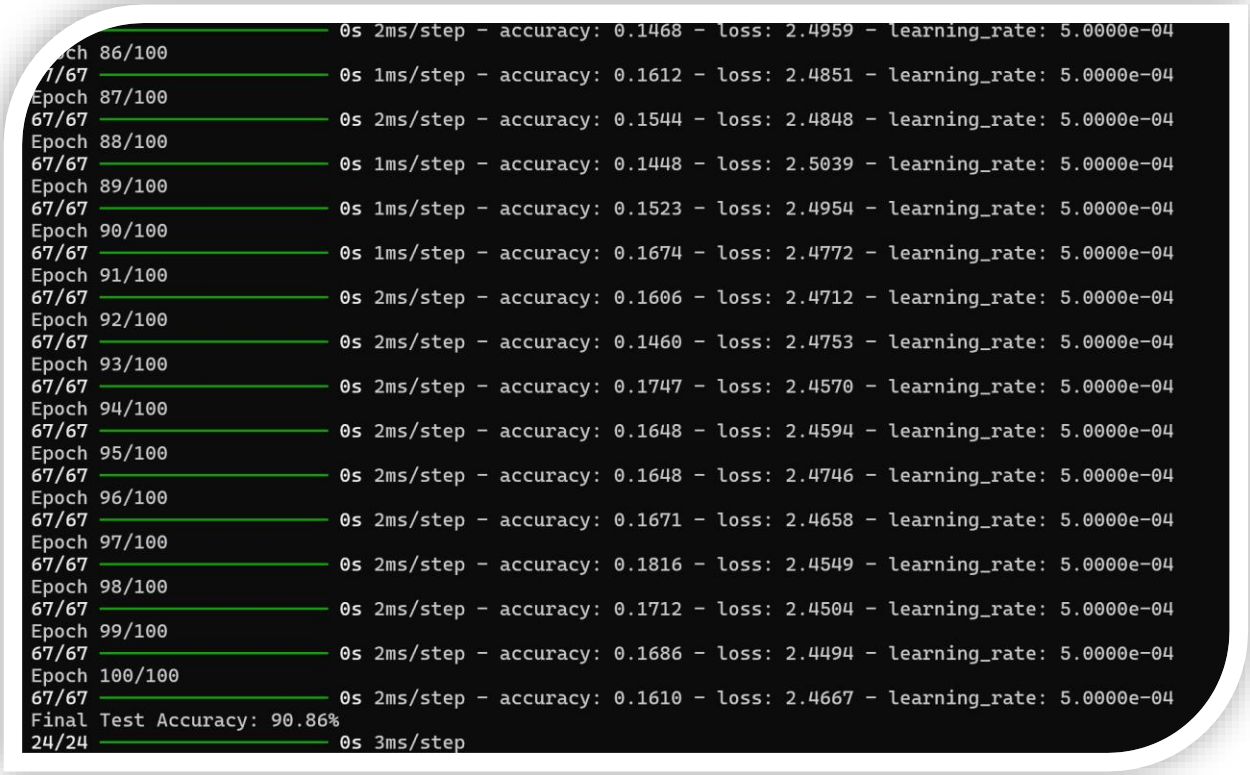

Figure 42: Final test accuracy of the Neural Network Model

- **Figure 42** shows the final test accuracy of the neural network model, which reached 90.86% after completing all training cycles. This high level of accuracy demonstrates the model's effectiveness in learning patterns and relationships from the data, enabling it to make reliable and personalized car recommendations based on user preferences. The consistency of this accuracy across cross-validation further confirms the model's stability, showing that it performs well on varied data samples and isn't overly reliant on any specific subset of the data.
- **Reflection on Results**: Achieving this accuracy was a key milestone, as it indicates that the model can handle the complexity of car attributes and user preferences while adapting to new inputs. The model's robustness through cross-validation suggests that it can be applied reliably in real-world scenarios, making accurate recommendations even as user preferences vary. This outcome highlights the importance of thorough data preparation, careful tuning, and systematic evaluation—all of which contributed to the model's strong performance.

These test results highlight the practical value of machine learning in creating useful, user-centred solutions, and it provided insights into how AI can simplify decision-making for users.

6.2 Personalized Car Recommendation with real life users - tests and results

Real life Testing of the system

User 1 - Mr. Jason Andrewartha (performance, brand value and safety focused user)

- Jason says *"Hi, I want a powerful diesel SUV that has a good brand name, good warranty and reliability. It should not be more than 3 years old and should strictly be a front wheel drive car".*
- Jason's personalized choices were chosen as selections for the model and the below car was recommended by the model.

User Feedback: Jason was really impressed with the recommended model.

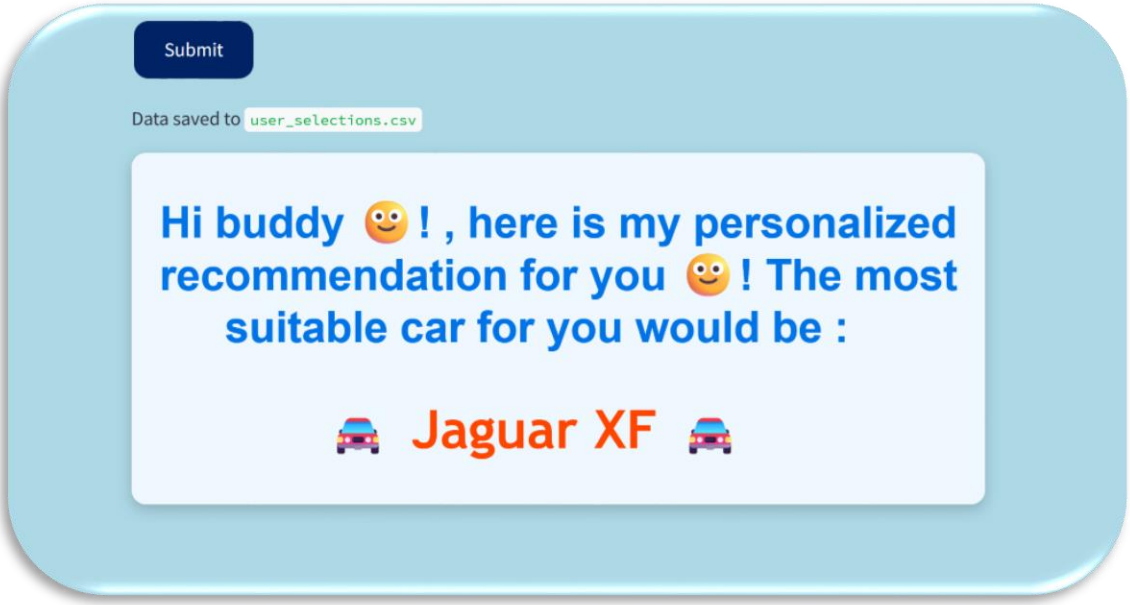

Figure 43: Real life system testing – User 1 – Jason

User 2 - Mr. Philip Henderson (Budget focused family-oriented user looking for efficiency)

- Philip says*, "I'm looking for an efficient and reliable family car with great fuel economy and a spacious interior. It should come with a good warranty, be within my budget, and should be a front-wheel drive for better fuel efficiency."*
- Philip's personalized choices were selected for the model, and the car recommendation provided by the model met all his preferences.

User Feedback: Philip was very satisfied with the recommended vehicle, appreciating its balance of affordability, efficiency, and reliability.

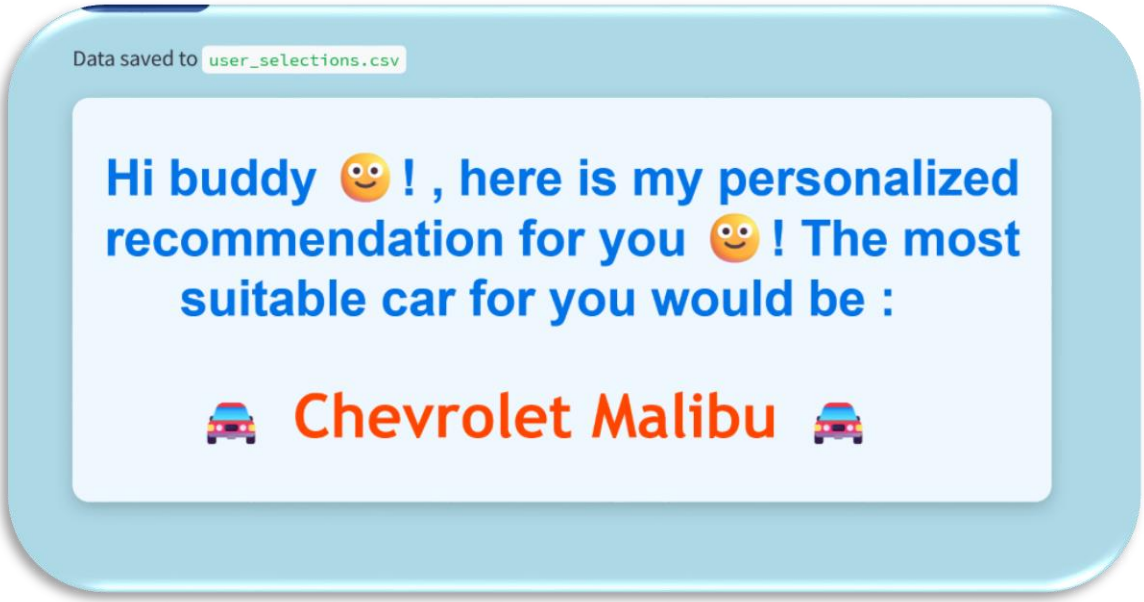

Figure 44: Real life system testing – User 2 – Philip

User 3 - Mr. Ronald Stevens (Comfort-focused user looking for a powerful yet cost-efficient SUV)

- Ronald says, *"I'm looking for a mid-size diesel SUV that is powerful but not too expensive to own and maintain. It should be spacious enough for 6 people and comfortable for long highway drives."*
- Ronald's personalized choices were selected for the model, and the recommended SUV matched his criteria perfectly.

User Feedback: Ronald was pleased with the balance of power, spacious interior, and overall comfort of the recommended vehicle, making it an ideal choice for both family trips and long drives.

Figure 45: Real life system testing – User 3 – Ronald

User 4 - Ms. Elena Vasquez (Eco-conscious city dweller looking for a stylish, eco-friendly electric car)

- Elena says, *"I want a compact, eco-friendly electric or a hybrid car that's easy to maneuver in the city. It should have good mileage, a sleek design, and modern features like parking assistance. Sustainability is important to me, but I also want it to look stylish and minimalist."*
- Elena's personalized choices were selected for the model, and the recommended electric car fit her vision perfectly.

User Feedback: Elena was thrilled with the stylish design, zero-emission engine, and advanced city-driving features of the recommended vehicle, making it the ideal choice for sustainable urban commuting.

Figure 46: Real life system testing – User 4 – Elena

The User feedback highlighted the ease of use and accessibility of the image-based selection interface. This positive reception confirms that the system's design choices successfully enhance engagement, making AI-driven recommendations easy to navigate for all users.

7. Future scope and plans for Expansion

The Car Purchase Recommendation System is currently a web-based application running locally for development and testing purposes. However, there are several ways to scale and extend its capabilities to reach a wider audience.

Figure 47: Image representing future scope and recommendations

Scaling, Dockerization, and Global Access

- At present, the system operates in a local environment.
- To prepare it for worldwide usage, the app can be **scaled and containerized** using **Docker**.
- Docker packages the entire application, including its dependencies, so that it can work consistently on different machines and environments.
- Once containerized, the system can be deployed on cloud platforms like **AWS**, **Google Cloud**, or **Azure** to enable global accessibility.
- This means people from any part of the world can easily access the app.
- Additionally, using tools like **Kubernetes** would help manage and scale the app automatically, making sure it performs efficiently even with high user traffic.

Figure 48: Image representing Scaling, Dockerization, and Global Access

Integration as an API or with Partner Platforms

- Beyond its current form as a web application, the recommendation system could also be offered as a **standalone API**.
- This means that other developers and businesses could integrate the recommendation features directly into their own platforms.
- For example, well-known automotive sites like **CarWow**, **Cars24.com**, or **Autocar.com** could use this system to enhance their existing platforms with smart, AI-driven car recommendations.
- Additionally, the app could be utilized internally by **car sales agents** or automotive review websites to offer personalized suggestions to customers, making it a valuable tool in their sales process.

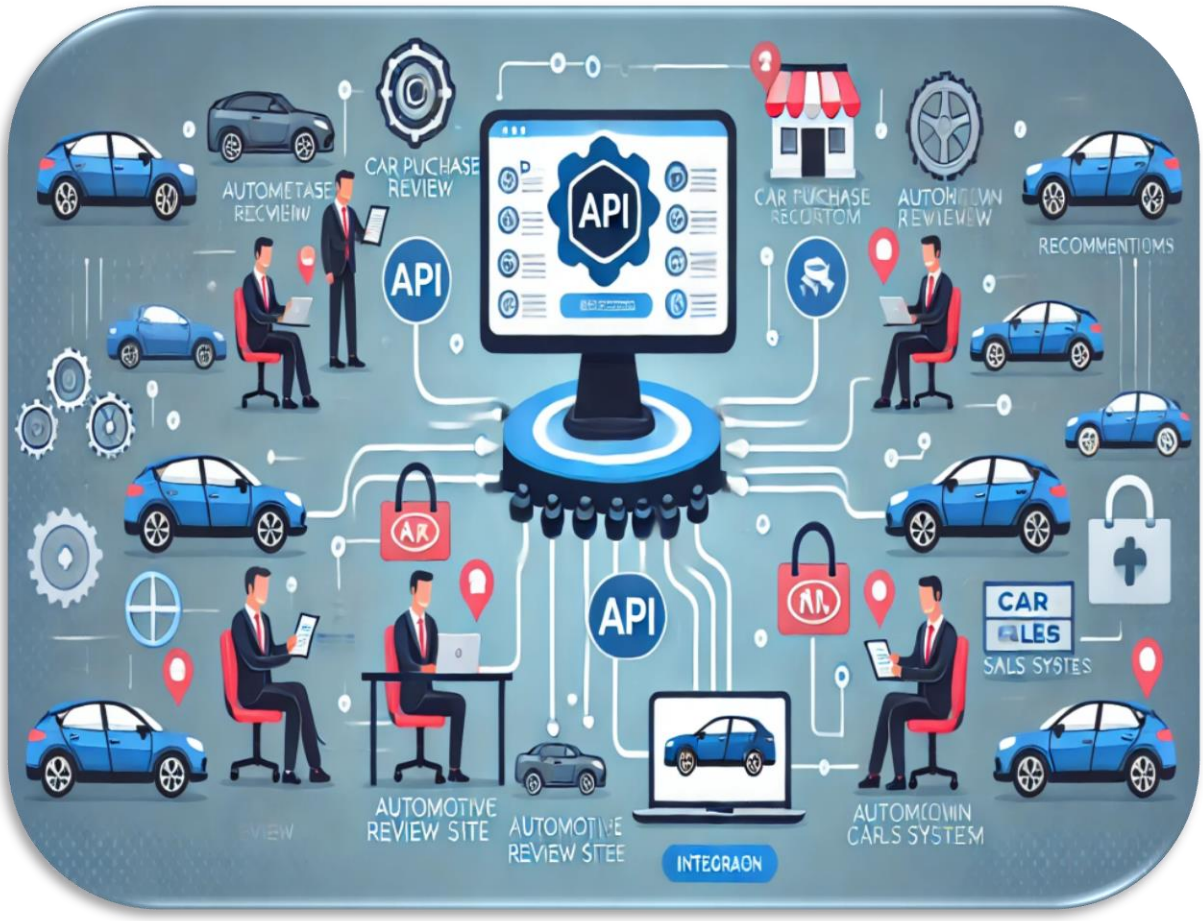

Figure 49: Image representing Integration as an API or with Partner Platforms

Building a Native Mobile App

- While the system is currently web-based, it could be transformed into a native mobile app using the same recommendation model.
- A mobile version would allow users to access the app directly from their smartphones or tablets, making it more convenient for people on the go.
- The mobile app could also take advantage of features like geolocation to recommend nearby car dealerships or showcase location-based deals, further improving the user experience.

Figure 50: Image representing a Native Mobile App platform

8. Conclusion

Developing the Car Purchase Recommendation System has been a rewarding journey that successfully met its goal of delivering personalized car suggestions based on each user's unique preferences. By combining a custom-built neural network model with an easy-to-use, interactive interface, the project shows how machine learning can help simplify the complex decision of buying a car. Coming from a software engineering background, diving into machine learning and data science allowed me to expand my technical skills and create a system that combines advanced technology with a strong focus on the user experience.

Throughout this project, each phase was carefully planned, from gathering and cleaning data to building and refining the model. Working with user-focused features, like fuel efficiency, safety, and brand value, helped the system generate accurate and relevant recommendations, reaching a **final test accuracy of 90.86%**. Applying methods such as Dropout, Batch Normalization, and Early Stopping not only improved the model but also deepened my understanding of how neural networks work, preparing me for more data-driven projects in the future. On the user interface side, Streamlit made it possible to design a clear, interactive experience where users could easily input their preferences through image-based options. Creating this intuitive front end taught me the value of making complex technology accessible, ensuring that even non-technical users could navigate the system comfortably. By presenting results in a simple, visually engaging way, the system bridges advanced AI with a smooth and enjoyable user experience.

The success of this project highlights how powerful AI can be when combined with careful design and thorough testing. Looking ahead, I see potential for even more growth and reach: deploying the system on cloud platforms via Docker for wider accessibility, and eventually offering it as an API that could be integrated into other platforms. Additionally, creating a mobile app version could make it even more convenient for users to get car recommendations anytime, anywhere.

This project reflects the intersection of machine learning, software engineering, and user-centred design. It's been an important step in my learning journey, expanding my skills in AI and data science while preparing me for future challenges. Not only does this system give users tailored car recommendations, but it also shows the potential of interactive, AI-driven tools to make big decisions like car buying easier, more efficient, and even enjoyable.

Overall, this project has not only expanded my skill set in AI and machine learning but has also shown me the potential of user-centred AI solutions to impact everyday decision-making. With a solid foundation now in machine learning and interactive applications, my goal is to explore advanced neural network architectures and work on AI tools that are both powerful and accessible. This experience has transformed my approach to problem-solving, encouraging me to continue developing applications that integrate sophisticated technology with a seamless user experience. The Car Purchase Recommendation System stands as a testament to this vision, demonstrating how thoughtfully designed AI can simplify complex processes like car selection, making them more personalized and enjoyable.

9. Appendix

9.1 Teamwork Breakdown

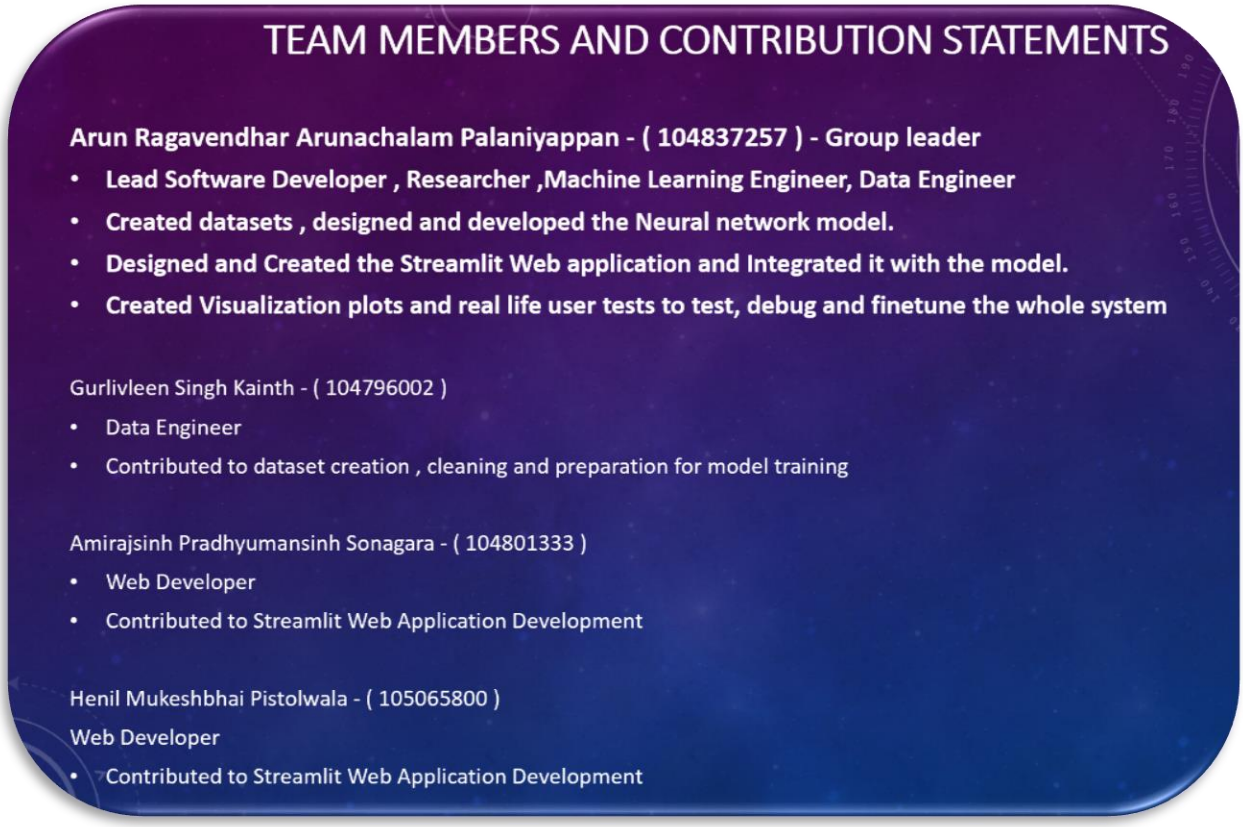

Figure 51: Teamwork breakdown showing the list of tasks done by each team member

9.2 Technical log entry

No.	Date Range	Task Description	Detailed Technical Log
1	23/09/2024 - 31/09/2024	**Creation of the Web Application using Streamlit**	Developed the initial structure of the web application in Streamlit, focusing on a user-friendly design that included image-based selection options for intuitive interaction. Key elements implemented included interactive buttons, form handling for user preferences, and layout optimization for mobile compatibility. The application interface was designed with accessibility and ease of use in mind, ensuring compatibility across various devices and screen sizes. Early testing was conducted to confirm UI responsiveness and smooth navigation, resulting in layout refinements based on initial feedback.
2	01/10/2024 - 07/10/2024	**Collecting, Cleaning, and Preparation of the Dataset**	Acquired raw data on car features from various online sources using BeautifulSoup for web scraping, focusing on essential attributes like car model, body type, engine type, and user ratings. The dataset was processed by addressing missing values (filled or removed as appropriate) and identifying outliers. Min-Max Scaling was applied to numerical fields (e.g., price, fuel economy) to standardize them within a 0 to 1 range, ensuring consistency for model training. Categorical attributes were converted through One-Hot Encoding to make them suitable for the neural

			network. The cleaned dataset comprised 10,000 records with 18 structured attributes, optimized for machine learning.
3	08/10/2024 - 14/10/2024	**System Design and Initial Setup of the ML Model**	Designed a Multi-Layer Perceptron (MLP) neural network model in TensorFlow. The architecture included three hidden layers (256, 128, and 64 neurons) with ReLU activation functions and HeNormal initialization to support efficient learning. Dropout layers were incorporated to prevent overfitting. Initial testing of the model focused on verifying the data flow and layer compatibility, ensuring that input dimensions matched the processed dataset. Adjustments were made based on preliminary runs to fine-tune model structure and optimize memory usage.
4	15/10/2024 - 21/10/2024	**Training and Fine-Tuning of the ML Model**	The MLP model was trained using the processed dataset in a 5-fold cross-validation setup. Dropout (40% in the first layer, 30% in subsequent layers) and Batch Normalization were applied to improve model robustness. Early Stopping was implemented to prevent overfitting, with training automatically stopping when no improvement was observed after a set number of epochs. The training process required multiple iterations, with adjustments to the learning rate and dropout rates to maximize accuracy. The final model achieved a test accuracy of 90.86%. Training logs and accuracy/loss curves were recorded for each fold to document performance.
5	22/10/2024 - 28/10/2024	**Integration of All Components (Web App, Dataset, ML Model)**	Integrated the trained neural network model with the Streamlit web application. Data flows were established to connect user inputs directly to the model, enabling real-time recommendations based on selected preferences. The dataset was loaded into the backend, and functions were set up to preprocess user input into the correct format for the model. User interactions were thoroughly tested to ensure seamless operation, and error handling was implemented to manage unexpected inputs. Modifications were made to improve response times and overall performance for real-time use.
6	22/10/2024 - 28/10/2024	**Testing and Debugging of the Complete System**	Conducted comprehensive system testing to ensure the accuracy of recommendations and the functionality of the user interface. Simulated diverse user interactions to verify the accuracy of the model's output based on varied inputs. Identified and resolved issues related to data format mismatches between user input and model requirements. User feedback led to UI refinements, such as repositioning buttons and enhancing image clarity. Model predictions were cross verified with test data to confirm reliability, achieving stable and accurate results.
7	29/10/2024 - 04/11/2024	**Final Report Preparation and Review**	Compiled a detailed project report covering the objectives, methodology, technical details, and outcomes. Ensured that each section provided a thorough explanation of the project stages, from data collection to model deployment. Incorporated feedback from peer reviews to improve structure and clarity. The report was finalized to align with marking criteria, including comprehensive reflections on learning outcomes, visualizations of results, and technical details in appendices.
8	29/10/2024 - 04/11/2024	**Project Live Demo and Presentation**	Prepared and delivered an in-person live demonstration of the project, showcasing the system's goals, implementation stages, and key achievements. This included a walkthrough of the Streamlit application's functionality and a review of the model's performance. Additionally, a comprehensive PowerPoint presentation was created to support the demonstration, highlighting essential aspects of the project. Finalized the project submission form, ensuring all documentation, technical logs, and deliverables were complete and well-organized for assessment by the tutor.

Table 5: Technical log entry with the list of tasks done with respective timelines

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