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COURSE: UNDERSTANDING ARTIFICIAL INTELLIGENCE.

Component One

Prediction of Sales Performance of Video Games with Machine Learning Models

Abstract

This study investigated the use of machine learning models, including regression, clustering, and neural networks, to predict global video game sales. Various models were evaluated using metrics such as RMSE, MAE, and R^2. Results showed that multiple linear regression and random forest achieved high accuracy, with R^2 values of 0.99 and 0.98, respectively. Among the artificial neural networks, Model 3 performed best with an MSE of 0.02. Unsupervised models, particularly agglomerative clustering, outperformed k-means. The findings demonstrate the effectiveness of machine learning in sales prediction, with future research focusing on the impact of categorical variables like genre and platform.

Keywords: Video Games, Sales performance, machine learning, artificial neural networks
Word count: 99

Introduction

1.1 Background to the Study

The video game industry has experienced significant growth in recent years. Factors such as genre, platform, publisher, and rating among others significantly influence sales performance worldwide (Vishwakarma & Kumari, 2024). As a result, video game companies and their customers have generated vast amounts of data. Machine learning techniques are highly efficient in extracting insights from large datasets (Li et al., 2021). This study employs various supervised learning, unsupervised learning, and deep learning models to predict the global sales performance of video games.

Literature Review

2.1 Related Studies

Li et al (2021) employed a hybrid feature selection using nine machine learning models to predict video game sales. Their results showed that their hybrid model performed better than single models in forecasting sales. Huang (2023) investigated various neural network models for predicting video game sales, revealing that XGBoost provided the best performance. Similarly, Vishwakarma and Kumari (2024) developed multiple linear regression models to predict video game sales.

Methodology

3.1 Machine Learning Techniques

This study utilized supervised learning techniques such as linear regression, multiple linear regression, and polynomial regression. These techniques were used to compare the impact of various features - including North American sales, European Sales, Japan Sales, other regional sales, genre, publisher, and platform - on Global Sales. Additionally, Unsupervised techniques such as k-means clustering and agglomerative clustering were employed to understand the influence of these factors in predicting global sales. Artificial neural networks were also explored.

3.2 Dataset

The dataset employed in this study was published by Ibrahim Muhammad Naeem on Kaggle, a verifiable data science platform. The dataset, which can be found here, [https://www.kaggle.com/datasets/ibriiee/video-games-sales-dataset-2022-updated-extra-feat], contained many null values which were dropped for an effective and clean dataset. The dataset was also examined for duplicated values but none was found. The dataset was formatted, cleaned, and hot encoded as required.

3.3 Exploratory Data Analysis

In this section, exploratory data analysis was carried out with visualizations using Python's Seaborn, matplotlib library using heatmaps and graphs, and boxplots to find correlations between variables of interest and detect potential outliers.

In Figure 1, sales across America, Japan, Europe, and other regions are illustrated. Video game sales peaked between 2005 and 2010 for all regions.

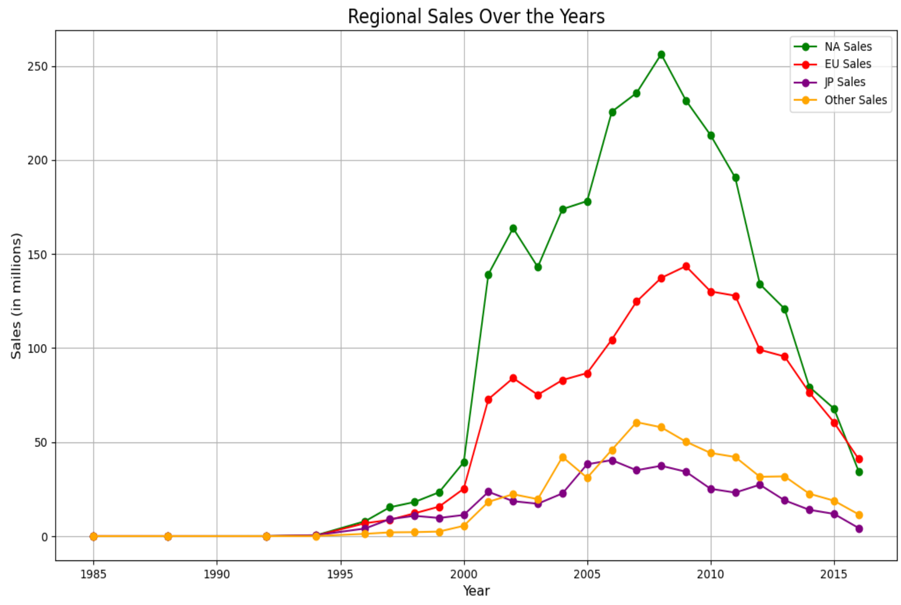

Figure 1: Number of games sold per year across North America, Japan, Europe, and other regions.

Correlation between the variables of interest revealed that sales in North America, Europe, Japan, and other regions were highly correlated with global sales with North America being the highest as illustrated in Figure 2.

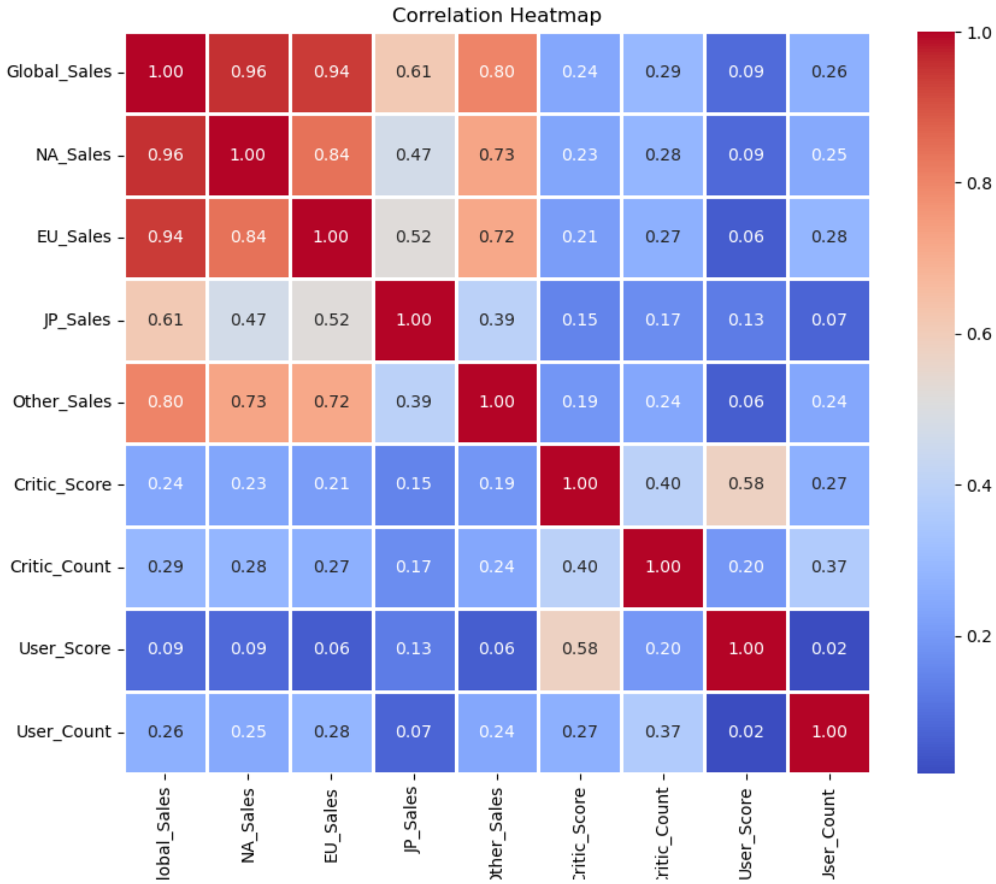

Figure 2: Correlation heatmap of variables of interest

Action-themed was the most played video game, followed by sports as illustrated by the count plot in Figure 3.

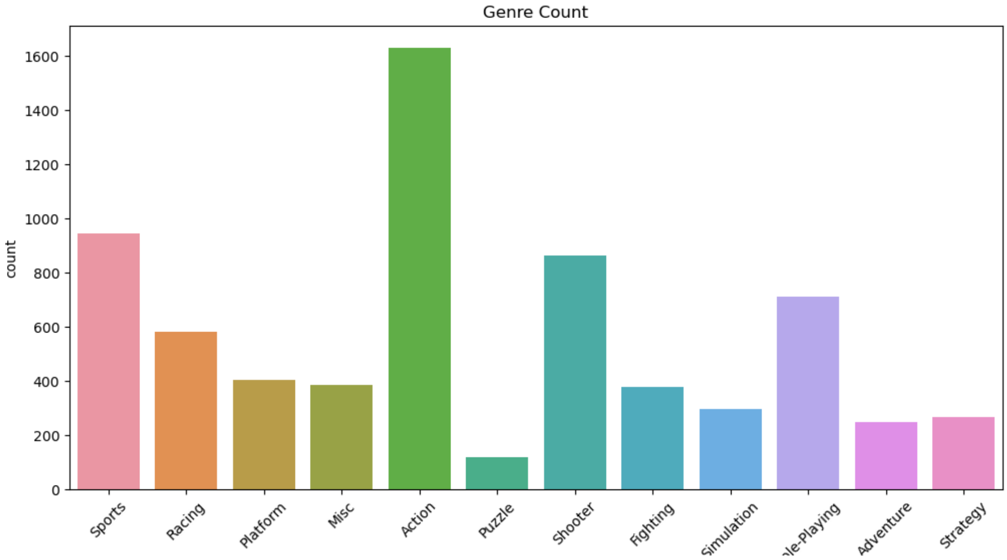

Figure 3: Count plot of video game genre

3.4 Brief Description of Machine Learning Models

Supervised Learning Techniques.

1. Simple Linear Regression: In machine learning, a simple linear regression is used to predict the relationship between two variables. To examine the continuous effect of the predictor variable on the target variable.

2. Polynomial Regression: This algorithm is well suited for datasets that are non-linear. As an extension of linear regression, it attempts to model the relationship between outcome and predictor variables.

3. Multiple Linear Regression: Similar to linear regression but with two or more input features (Predictors) to examine their influence on an outcome variable.

Unsupervised Learning Techniques

1. K-Means Clustering: This algorithm attempts to find clusters within data and groups them into k partitions based on their attributes. It uses the elbow method to find the optimal number of clusters.

2. Agglomerative Clustering: This algorithm employs a bottom-up approach where each cluster is considered as a tiny cluster and the two closest clusters are combined into a new aggregated cluster.

Deep Learning Models

Artificial Neural Network (ANN): An Artificial Neural Network (ANN) is a computational model inspired by the structure of biological neural networks in the human brain. They consist of layers of interconnected nodes (also called neurons), where each connection represents a weight that adjusts as learning proceeds. These networks are used to approximate complex functions and solve problems in various domains, such as classification, regression, and pattern recognition (Goodfellow, 2016). They can be applied to supervised, and unsupervised tasks.

Results

This section presents the findings of the analysis of various models. For the supervised learning models, the R^2 Coefficient, Root Mean Square Error, and Absolute Mean Square were used to evaluate the performance of the linear regression model. These input features were chosen based on the correlation matrix in Figure 2.

Table 1. Linear Regression Analysis Predicting Global Sales.

Performance Metrics	NA Sales	EU Sales	JP Sales	Other sales
Root Mean Square Error (RMSE)	0.37	0.41	2.10	0.82
Mean Absolute Error (MAE)	0.25	0.31	0.69	0.38
R^2 Score	0.86	0.85	0.23	0.70

The analysis of the linear regression model presented in Table 1 shows that North American sales best predict global sales with an R^2 (0.86) accounting for 86% variation in global sales. The lowest RMSE (0.37) and MAE (0.25) explain better model performance.

Table 2. Polynomial Regression Analysis Predicting Global Sales.

Performance Metrics	NA Sales	EU Sales	JP Sales	Other sales
Root Mean Square Error (RMSE)	0.36	0.41	2.15	0.76
Mean Absolute Error (MAE)	0.25	0.31	0.69	0.33
R^2 Score	0.87	0.85	0.21	0.72

The analysis of the polynomial regression model presented in Table 2 shows that North American sales best predict global sales with an R^2 (0.87) accounting for 87% variation in global sales. The lowest RMSE (0.36) and MAE (0.25) explain better model performance.

The global sales is best fit by a linear model as shown in the graphs plotted in the accompanying Jupyter Notebook file.

Table 3. Multiple Linear Regression Analysis Predicting Global Sales.

Performance Metrics	Values
Root Mean Square Error (RMSE)	0.006
Mean Absolute Error (MAE)	0.003
Mean Square Error (MSE)	3.66
R^2 Score	0.99

R^2 (0.99) shows that the multiple input features combined account for 99% variance in global sales, as shown in Table 3. The low RMSE (0.006) and MAE (0.003) reveal that it performed better than the previous linear regression model with improved accuracy.

Table 4. Random Forest Regression Analysis Predicting Global Sales.

Performance Metrics	Values
Root Mean Square Error (RMSE)	0.05
Mean Absolute Error (MAE)	0.05
R^2 Score	0.98

Table 4 presents the results of the Random Forest Regressor which included categorical variables such as genre, platform, and publisher combined with other relevant numeric features. The model achieved an R^2 (0.98) showing that combined features account for 98% variance in global sales. The low RMSE (0.05) and MAE (0.05) reveal that it performed better than the previous linear regression model with improved accuracy.

Table 5 Artificial Neural Network Analysis

Performance Metrics	Model 1	Model 2	Model 3	Model 4
MSE (Training)	0.05	0.35	0.02	0.10
MSE (Validation)	0.008	0.29	0.008	0.05
Epoch Trained (Early Stopping)	43	36	37	47
Learning Rate (Adam Optimizer)	0.001	0.01	0.001	0.001

The ANN models were built using an input layer that had four input dimensions according to the number of predictor variables used. Each model had an input layer, a hidden layer, and outer layer. ReLU activation was used for the input and hidden layers while the linear activation function was used in the outer layer since the task involved continuous regression. Mean Square error was used to compare the performance of the models with various learning rates.

As shown in Table 5, the third ANN model performed best with an MSE of 0.02. Compared to the previous linear regression models, it performed better with a line of fit that cut across both actual and predicted values as shown in Figure 3.

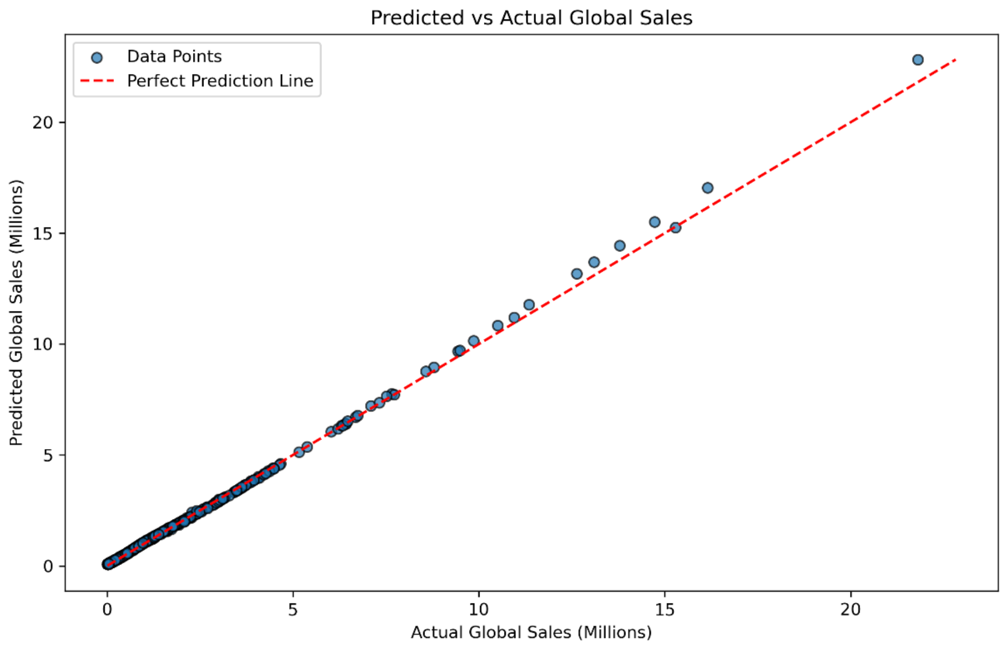

Figure 3: Line of best-fit ANN Model 3

The K-means clustering method was also employed in the analysis to find the best clusters. Two different combinations of numeric features were explored and the elbow method was explored to find the number of clusters to use. The evaluation metrics for the algorithm was Davies Bouldin and Silhouette Coefficient.

Table 6. Unsupervised Learning Techniques Analysis

Performance Metrics	**KNN Model 1**	**KNN Model 2**	**Agglomerative Model 1**	**Agglomerative Model 2**
Davies Bouldin Score	0.47	0.39	0.45	0.32
Silhouette Coefficient	0.82	0.90	0.92	0.93
Number of Clusters	4	3	4	3

The combination of global sales and North American sales produced the best result for the k-means clustering algorithm with a silhouette coefficient of 0.90 and a Davies Bouldin score of 0.39 which shows data points are closer to their clusters than others.

The agglomerative model outperformed the k-means with a silhouette coefficient of 0.93 and a Davies Bouldin score of 0.32.

Discussion

The linear regression model performed well in predicting global sales with the multiple linear regression achieving the highest r2 score. In line with the result from Vishwakarma and Kumari (2024), regression models can predict global video game sales. Furthermore, the artificial neural networks also excelled at predicting global sales with reliable results which conforms with the results of Li et al (2021).

Conclusion

This study investigates various machine learning models for predicting the global sales of video games using selected features. The findings demonstrate that several models perform exceptionally well in sales prediction. Future research will focus on examining the influence of categorical variables, such as genre and platform, in greater detail.

Component Two

Emergency Vehicle Image Classification using Convolutional Neural Network Architecture with Hyperparameter Tuning

Abstract

This study investigates the use of convolutional neural networks (CNNs) to classify emergency and non-emergency vehicles, aiming to improve traffic management during emergencies. Using a dataset of 1,646 labeled images, CNN models were developed, with the best-performing model achieving 83% accuracy. While the model effectively identified non-emergency vehicles, its recall for emergency vehicles was lower. The results highlight CNNs' potential for real-world applications in traffic systems, with future improvements possible through techniques like transfer learning.

Keywords: Convolutional neural network, emergency vehicle classification, binary classification
Word Count: 75

Introduction

1.1 Background of the Study

In recent times, there has been an increase in the number of cars on the roads globally. According to a report by the World Economic Forum (2016), this is set to double by 2040. Therefore, it has become imperative to clear traffic congestion to enable emergency vehicles to reach their destination in time. Deep learning, particularly convolutional neural network architecture in computer vision, has garnered attention in recent years (Jahan et al., 2020). Emergency vehicles, including ambulances, firetrucks, police vehicles, and others, must be effectively distinguished from regular vehicles on the road (Deepajothi et al., 2021). To improve the chances of clearing traffic congestion during emergencies and reducing fatalities, convolutional neural networks are being increasingly utilized for their exceptional ability to capture patterns in images and classify objects, addressing real-world challenges.

Objective of the Study

2.1 Aim and Objective

This study aims to develop and train convolutional neural networks with hyperparameter tuning and apply the best-performing model to unseen images of emergency and non-emergency vehicles to achieve high accuracy.

Literature Review

3.1 Related Studies

Several scholars have worked on developing convolutional neural network models to address this real-world problem. For example, Alaoui et al. (2023) designed a pre-trained convolutional neural network to classify images as either emergency vehicles or non-emergency vehicles. Similarly, Deepajothi et al. (2021) proposed a convolutional neural network to improve traffic management systems.

Methodology

This section provides a brief overview of the methodology used to build and apply the convolutional neural network

4.1 Data Collection and Preprocessing

The Data was obtained from Kaggle, an open-source data science repository. The dataset contained 1646 images with corresponding labels of not emergency and emergency distinguished as 0 and 1 respectively.

The Data was pre-processed by checking for duplicated and missing or null values which contained none. To enhance generalization, Keras's image generator was used for data augmentation, applying 20° rotation, 10% horizontal and vertical shifts, 10% cropping, and 10% zooming. The images retained their original size with a shape of 224x224x3 pixels, as illustrated in Figure 1.

```
The x_train shape is: (1316, 224, 224, 3)
The x_test shape is: (330, 224, 224, 3)
The y_train shape is: (1316,)
The y_test shape is: (330,)
```

Figure 1: Input Image Shape (Adejuwon, 2024)

Min-Max normalization was applied to scale pixel values to a range of 0 to 1 by dividing them by 255. The dataset was split into 80% training and 20% testing to ensure a sufficient amount of data for the model to learn effectively while reserving an adequate portion for evaluating the model's performance on unseen data. The 80-20 split is a common practice in machine learning, striking a balance between training the model and reliably assessing its generalization ability.

4.2 Model Development

There are four stages in the construction of a convolutional neural network. They are as follows:

- The Construction Stage
- The Compilation Stage
- The Training Stage
- The Evaluation Stage

The basic architecture of a convolutional neural network includes an input layer, at least three 2D convolutional blocks each with ReLU activation and pooling, a flatten layer to convert images into 1D, and a fully connected (dense) layer. The output layer comprises neurons with an activation function suitable for the classification task. This structure, shown in Figure 2, was used in the emergency vehicle classification models.

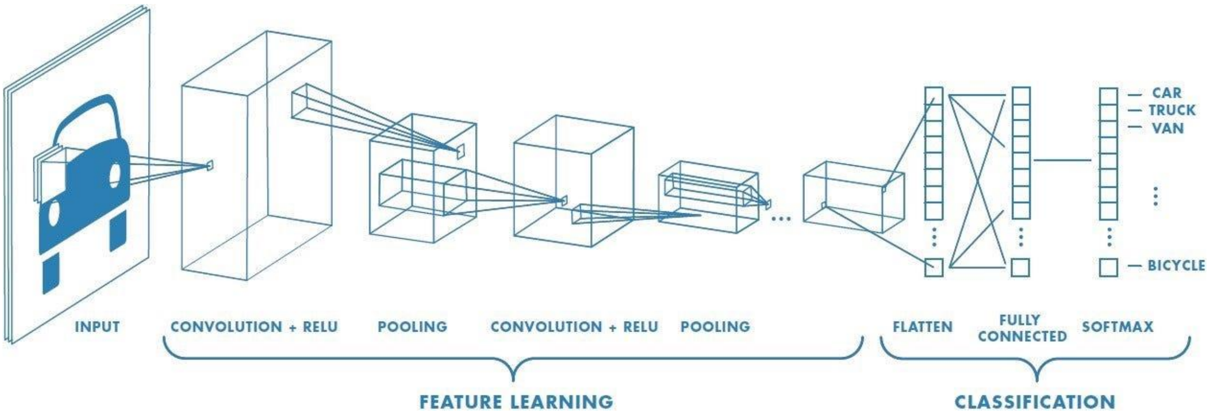

Figure 2: Convolution neural network architecture by IBM (2022)

Results

In the emergency vehicle classification task, seven models were built with various hyperparameter tuning. Model 1 achieved the highest accuracy and F1 score.

Model 1: The architecture began with an input layer of shape (224, 224, 3) to accommodate height, width, and RGB-colored images. It featured three convolutional blocks with 32, 64, and 128 filters, each using ReLU activation and maximum pooling and a kernel size of (3,3) for horizontal and width for feature learning. A flattening layer converted the output into 1D, followed by a dense layer, a dropout regularization to control for overfitting, and a single-neuron output layer with a sigmoid activation function for the probability binary classification as illustrated in Figure 3.

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 222, 222, 32)	896
max_pooling2d (MaxPooling2D)	(None, 111, 111, 32)	0
conv2d_1 (Conv2D)	(None, 109, 109, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 54, 54, 64)	0
conv2d_2 (Conv2D)	(None, 52, 52, 128)	73,856
max_pooling2d_2 (MaxPooling2D)	(None, 26, 26, 128)	0
flatten (Flatten)	(None, 86528)	0
dense (Dense)	(None, 64)	5,537,856
dropout (Dropout)	(None, 64)	0
dense_1 (Dense)	(None, 1)	65

Total params: 5,631,169 (21.48 MB)

Trainable params: 5,631,169 (21.48 MB)

Non-trainable params: 0 (0.00 B)

Figure 3: Sequential Model Output (Adejuwon, 2024)

The model was compiled with an Adam optimizer with the default learning rate of 0.001, the loss function used was binary cross entropy and accuracy was the metrics.

```
Model compiled with optimizer=adam, loss=binary_crossentropy, metrics=['accuracy']
<Sequential name=sequential, built=True>
```

Figure 4: Model Compilation Output (Adejuwon, 2024)

The model was trained for 20 epochs as shown in Figure 5:

```
Epoch 1/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 204s 4s/step - accuracy: 0.5669 - loss: 0.9051 - val_accuracy: 0.6970 - val_loss: 0.6043
Epoch 2/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 149s 4s/step - accuracy: 0.7248 - loss: 0.5665 - val_accuracy: 0.7394 - val_loss: 0.5273
Epoch 3/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 149s 4s/step - accuracy: 0.7439 - loss: 0.5379 - val_accuracy: 0.6788 - val_loss: 0.5663
Epoch 4/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 150s 4s/step - accuracy: 0.7387 - loss: 0.5320 - val_accuracy: 0.7636 - val_loss: 0.5097
Epoch 5/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 154s 4s/step - accuracy: 0.7557 - loss: 0.5425 - val_accuracy: 0.7485 - val_loss: 0.5596
Epoch 6/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 151s 4s/step - accuracy: 0.7588 - loss: 0.4982 - val_accuracy: 0.8000 - val_loss: 0.4716
Epoch 7/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 151s 4s/step - accuracy: 0.7806 - loss: 0.4749 - val_accuracy: 0.7727 - val_loss: 0.4712
Epoch 8/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 165s 4s/step - accuracy: 0.7633 - loss: 0.5057 - val_accuracy: 0.7788 - val_loss: 0.4568
Epoch 9/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 150s 4s/step - accuracy: 0.7794 - loss: 0.4876 - val_accuracy: 0.7818 - val_loss: 0.4433
Epoch 10/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 150s 4s/step - accuracy: 0.7919 - loss: 0.4686 - val_accuracy: 0.8030 - val_loss: 0.4213
Epoch 11/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 156s 4s/step - accuracy: 0.8239 - loss: 0.4385 - val_accuracy: 0.7667 - val_loss: 0.4392
Epoch 12/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 151s 4s/step - accuracy: 0.8130 - loss: 0.4081 - val_accuracy: 0.7970 - val_loss: 0.3942
Epoch 13/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 150s 4s/step - accuracy: 0.7900 - loss: 0.4495 - val_accuracy: 0.7970 - val_loss: 0.4400
Epoch 14/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 149s 4s/step - accuracy: 0.7759 - loss: 0.4374 - val_accuracy: 0.8000 - val_loss: 0.4419
Epoch 15/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 150s 4s/step - accuracy: 0.8283 - loss: 0.3920 - val_accuracy: 0.7545 - val_loss: 0.5576
Epoch 16/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 152s 4s/step - accuracy: 0.8122 - loss: 0.4288 - val_accuracy: 0.8000 - val_loss: 0.4019
Epoch 17/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 151s 4s/step - accuracy: 0.8293 - loss: 0.4043 - val_accuracy: 0.8152 - val_loss: 0.3933
Epoch 18/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 150s 4s/step - accuracy: 0.8380 - loss: 0.3691 - val_accuracy: 0.7909 - val_loss: 0.3900
Epoch 19/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 151s 4s/step - accuracy: 0.8262 - loss: 0.3967 - val_accuracy: 0.8182 - val_loss: 0.4066
Epoch 20/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 151s 4s/step - accuracy: 0.8480 - loss: 0.3672 - val_accuracy: 0.8303 - val_loss: 0.4037
```

Figure 5: Epoch training of Model (Adejuwon, 2024)

The Training Loss and Accuracy were plotted as illustrated in Figures 6 & 7.

Figure 6: Training and Validation Loss (Adejuwon, 2024)

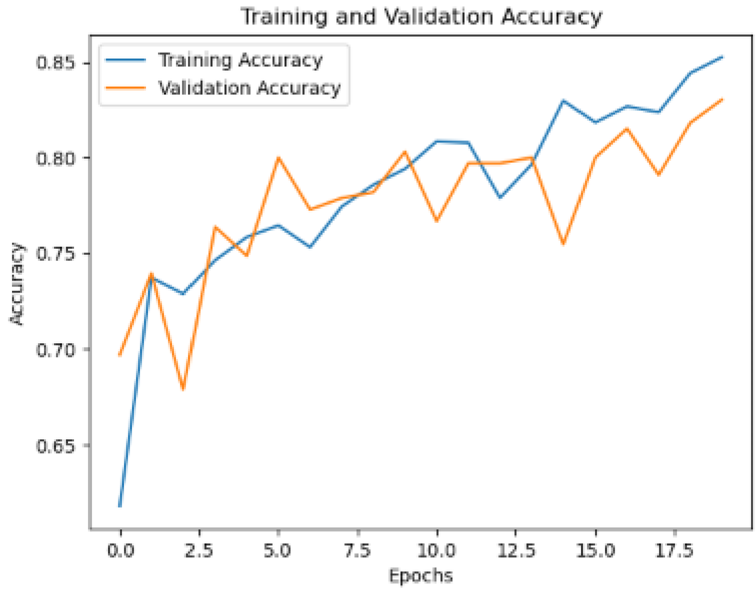

Figure7: Training and Validation Accuracy (Adejuwon, 2024*)*

The model was used to predict the test data. A classification report was generated with a confusion matrix showing the True Positives, True Negatives, False Positives, and False Negatives as shown in Figure 8.

```
Classification Report:
              precision    recall  f1-score   support

           0       0.81      0.94      0.87       198
           1       0.88      0.67      0.76       132

    accuracy                           0.83       330
   macro avg       0.84      0.80      0.81       330
weighted avg       0.84      0.83      0.82       330

<Figure size 2000x3000 with 0 Axes>
```

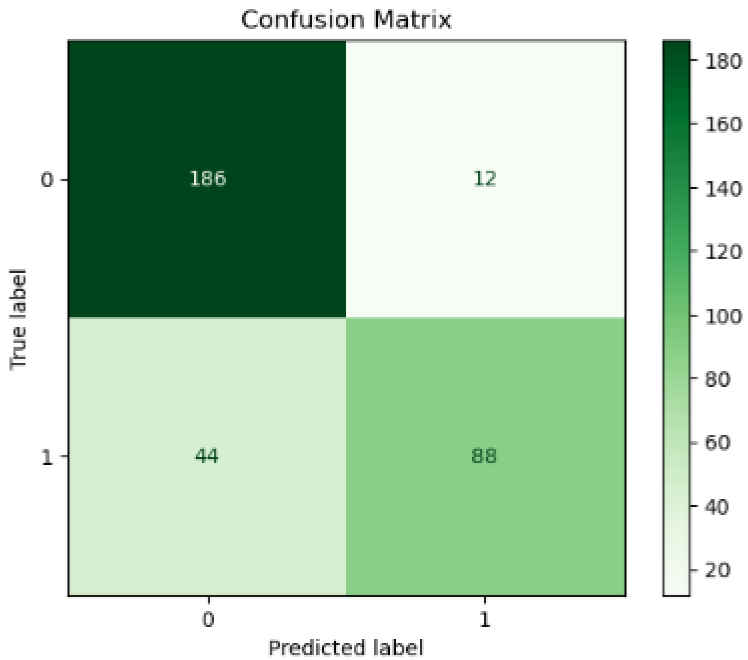

Figure 8: Classification Report and Confusion Matrix (Adejuwon, 2024*)*

The model performs well with an overall accuracy of 83%, showing high precision (0.81) and recall (0.94) for non-emergency vehicles (Class 0). For emergency vehicles (Class 1), precision is strong (0.88), but recall is lower (0.67), indicating many emergency vehicles are missed. The confusion matrix reveals 88 true positives, 12 false positives, 186 true negatives, and 44 false negatives, highlighting some misclassification between the two classes. Overall, the model excels in identifying non-emergency vehicles but needs improvement in detecting emergency vehicles.

Custom Model 2: Model 2 consists of three convolutional blocks with 32, 64, and 128 filters, each using a (5, 5) kernel size for feature extraction in both horizontal and vertical directions. Each block employs the ReLU activation function and MaxPooling for dimensionality reduction. Following the convolutional layers, a flatten layer converts the output into a 1D vector, which is passed through two dense layers for high-level representation learning. The output layer contains a single neuron with a Sigmoid activation function, making the model suitable for binary classification task.

The model was compiled using the Adam optimizer, binary cross-entropy loss, and accuracy as the evaluation metric.

The model was trained for 20 epochs with a batch size of 64. The batch size of 64 was chosen to balance training speed and model performance, allowing the model to process a sufficient number of samples per iteration while maintaining stable gradient updates.

The training evaluation is shown in Figure 9 below.

	accuracy	loss	val_accuracy	val_loss
0	0.556991	0.698876	0.663636	0.647820
1	0.680091	0.643051	0.703030	0.596732
2	0.709726	0.595845	0.718182	0.550421
3	0.750000	0.542613	0.757576	0.522355
4	0.743921	0.538993	0.748485	0.561209
5	0.740122	0.535428	0.751515	0.500181
6	0.753799	0.515073	0.742424	0.512888
7	0.768237	0.498448	0.745455	0.492066
8	0.781915	0.475624	0.793939	0.432623
9	0.801672	0.445914	0.760606	0.493483
10	0.794073	0.447707	0.775758	0.457366
11	0.797112	0.433301	0.827273	0.404813
12	0.798632	0.434511	0.818182	0.391567
13	0.814590	0.418948	0.809091	0.396639
14	0.812310	0.412525	0.803030	0.391399
15	0.831307	0.396271	0.775758	0.426238
16	0.824468	0.405372	0.830303	0.365792
17	0.830547	0.381950	0.778788	0.430145
18	0.818389	0.400524	0.821212	0.366557
19	0.849544	0.359071	0.821212	0.432934

Figure 9: Training and Validation accuracy and loss (Adejuwon, 2022)

Figure 10: Training and Validation Loss (Adejuwon, 2024)

The Graph in Figure 10 shows that the training loss steadily decreases which shows the model is learning well. The validation loss follows the same trend but with fluctuations as the epoch progresses, suggesting that the model struggles with generalization.

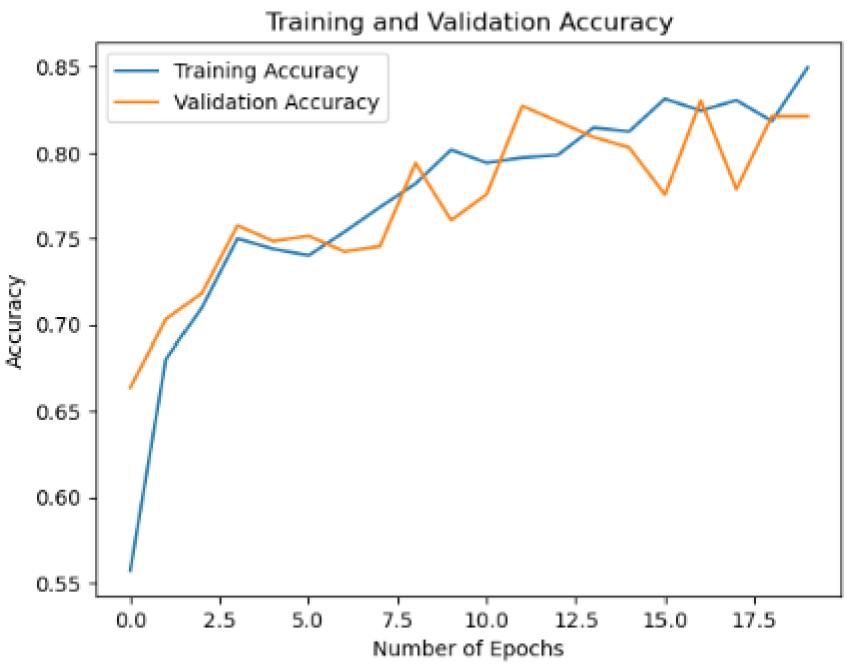

Figure 11: Training and Validation Accuracy (Adejuwon, 2024)

The Graph in Figure 11 shows that the training accuracy steadily increases over the epochs, suggesting effective learning. The validation accuracy follows the same trend but experiences fluctuations as the epoch progresses, suggesting that the model attempts to improve its ability to generalize to new, unseen data. The fluctuations in validation indicate further hyperparameter tuning might be essential.

The model was used to predict the test data. A classification report was generated with a confusion matrix showing the True Positives, True Negatives, False Positives, and False Negatives as shown in Figure 12.

```
Classification Report:
              precision    recall  f1-score   support

           0       0.78      0.97      0.87       198
           1       0.94      0.59      0.73       132

    accuracy                           0.82       330
   macro avg       0.86      0.78      0.80       330
weighted avg       0.84      0.82      0.81       330


<Figure size 2000x3000 with 0 Axes>
```

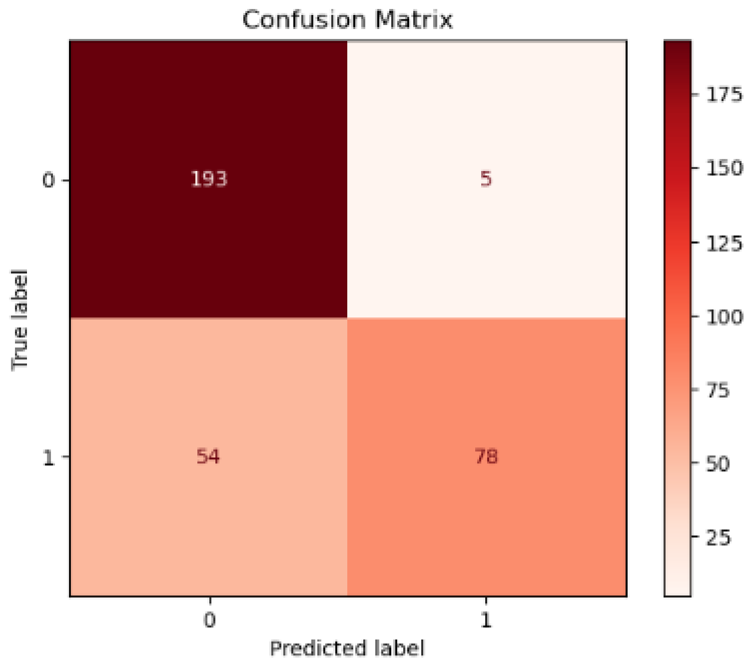

Figure 12: Classification Report and Confusion Matrix (Adejuwon, 2024)

The model performs well with an overall accuracy of 82%, showing high precision (0.78) and recall (0.97) for non-emergency vehicles (Class 0). For emergency vehicles (Class 1), precision is strong (0.94), but recall is lower (0.59), indicating many emergency vehicles are missed. The confusion matrix reveals 78 true positives, 5 false positives, 193 true negatives, and 54 false negatives, highlighting some misclassification between the two classes. Overall, the model excels in identifying non-emergency vehicles but needs improvement in detecting emergency vehicles.

Model 3: The third model followed the same architecture as the first model but was tuned using hyperparameters such as a kernel size of (5,5), padding that was set to the same, and batch normalization after each convolution block with a momentum of 0.9 to improve generalization. A dropout of 50% was included to prevent overfitting.

The model was compiled with an Adam optimizer with a learning rate of 0.01, a loss function of binary cross entropy since it's a binary classification task and a metric of accuracy.

The model was trained for 20 epochs as illustrated in Figure 13.

```
Epoch 1/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 511s 10s/step - accuracy: 0.5854 - loss: 2.6110 - val_accuracy: 0.6152 - val_loss: 1.2256
Epoch 2/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 391s 9s/step - accuracy: 0.5665 - loss: 0.9307 - val_accuracy: 0.6000 - val_loss: 0.6829
Epoch 3/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 388s 9s/step - accuracy: 0.5928 - loss: 0.6606 - val_accuracy: 0.6030 - val_loss: 0.6284
Epoch 4/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 389s 9s/step - accuracy: 0.5778 - loss: 0.6388 - val_accuracy: 0.5970 - val_loss: 0.6066
Epoch 5/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 389s 9s/step - accuracy: 0.6193 - loss: 0.5997 - val_accuracy: 0.7121 - val_loss: 0.6376
Epoch 6/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 388s 9s/step - accuracy: 0.6921 - loss: 0.6006 - val_accuracy: 0.7515 - val_loss: 0.5790
Epoch 7/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 388s 9s/step - accuracy: 0.6802 - loss: 0.5734 - val_accuracy: 0.7394 - val_loss: 0.7294
Epoch 8/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 388s 9s/step - accuracy: 0.7104 - loss: 0.5855 - val_accuracy: 0.7303 - val_loss: 0.6278
Epoch 9/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 388s 9s/step - accuracy: 0.6619 - loss: 0.6307 - val_accuracy: 0.6667 - val_loss: 0.7438
Epoch 10/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 388s 9s/step - accuracy: 0.6619 - loss: 0.6505 - val_accuracy: 0.7697 - val_loss: 0.5390
Epoch 11/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 388s 9s/step - accuracy: 0.6960 - loss: 0.5745 - val_accuracy: 0.7727 - val_loss: 0.5367
Epoch 12/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 387s 9s/step - accuracy: 0.6865 - loss: 0.5678 - val_accuracy: 0.7000 - val_loss: 0.5837
Epoch 13/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 388s 9s/step - accuracy: 0.7129 - loss: 0.5615 - val_accuracy: 0.7576 - val_loss: 0.5528
Epoch 14/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 388s 9s/step - accuracy: 0.7012 - loss: 0.5787 - val_accuracy: 0.6939 - val_loss: 0.7195
Epoch 15/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 386s 9s/step - accuracy: 0.7231 - loss: 0.5864 - val_accuracy: 0.7091 - val_loss: 0.5746
Epoch 16/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 389s 9s/step - accuracy: 0.6546 - loss: 0.6022 - val_accuracy: 0.7697 - val_loss: 0.5297
Epoch 17/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 388s 9s/step - accuracy: 0.7044 - loss: 0.5776 - val_accuracy: 0.7636 - val_loss: 0.5351
Epoch 18/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 387s 9s/step - accuracy: 0.7007 - loss: 0.5704 - val_accuracy: 0.7121 - val_loss: 0.5833
Epoch 19/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 389s 9s/step - accuracy: 0.7303 - loss: 0.5629 - val_accuracy: 0.6909 - val_loss: 0.5574
Epoch 20/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 390s 9s/step - accuracy: 0.7048 - loss: 0.5793 - val_accuracy: 0.7879 - val_loss: 0.5553
```

Figure 13: Epoch Training of Model (Adejuwon, 2024)

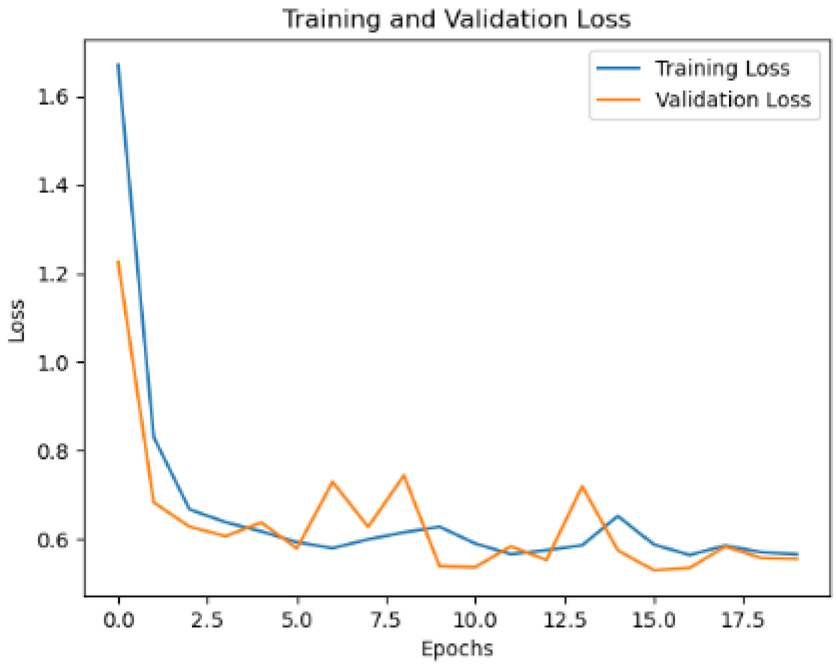

Figure 14: Training and Validation Loss (Adejuwon, 2024)

The Graph in Figure 14 shows that the training loss steadily decreases over the epochs, suggesting effective learning. The validation loss follows the same trend but experiences fluctuations as the epoch progresses, suggesting that the model struggles as it attempts to improve its ability to generalize to new, unseen data.

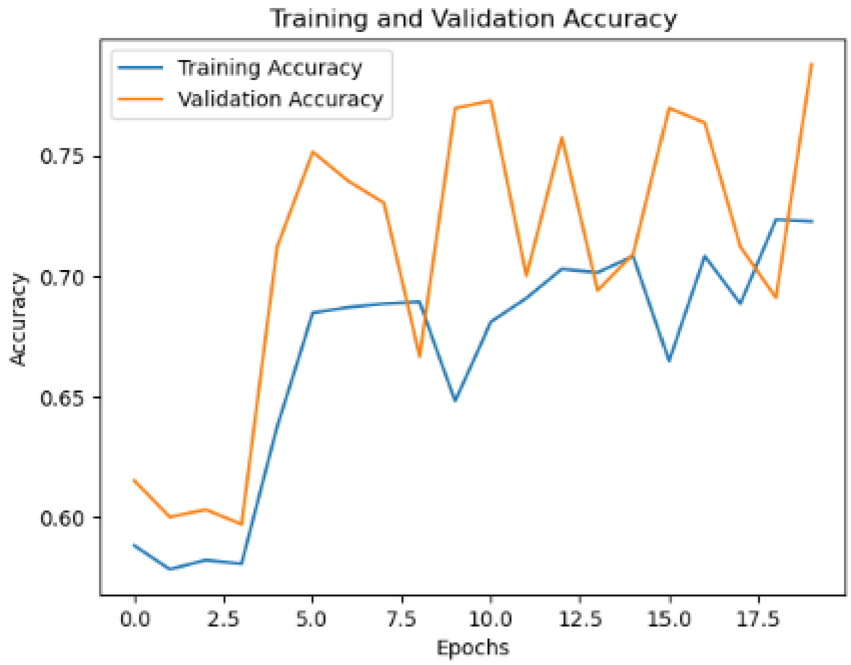

Figure 15: Training and Validation Accuracy (Adejuwon, 2024)

The Graph in Figure 15 shows that the training accuracy fluctuates as it increases over the epochs. The validation accuracy follows the same trend, suggesting that the model struggles to generalize to new, unseen data. The fluctuations in validation indicate a high learning rate which can cause the model's weights to update too aggressively.

The model was used to predict the test data. A classification report was generated with a confusion matrix showing the True Positives, True Negatives, False Positives, and False Negatives as shown in Figure 16.

```
Classification Report:
              precision    recall  f1-score   support

           0       0.81      0.85      0.83       198
           1       0.75      0.70      0.72       132

    accuracy                           0.79       330
   macro avg       0.78      0.77      0.78       330
weighted avg       0.79      0.79      0.79       330


<Figure size 2000x3000 with 0 Axes>
```

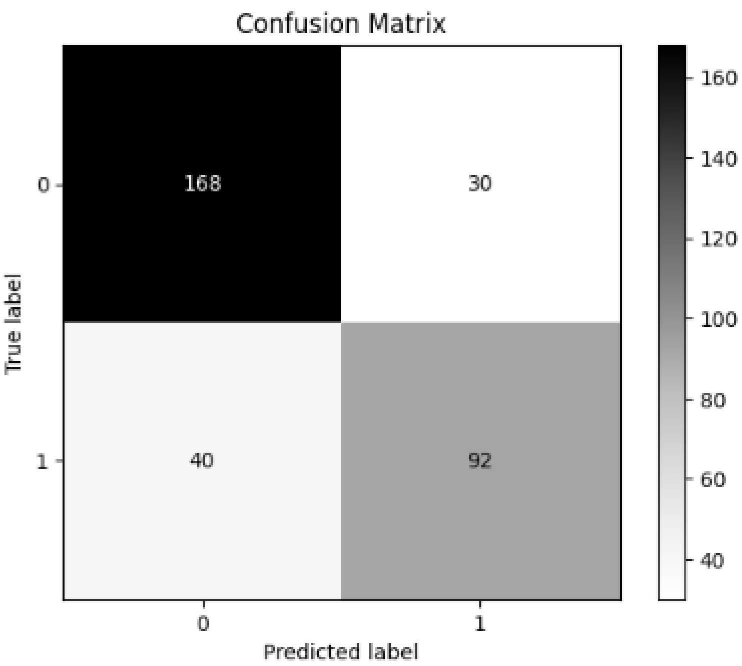

Figure 16: Classification and Confusion Matrix (Adejuwon, 2024*)*

The model performs well with an overall accuracy of 0.80%, showing high precision (0.81) and recall (0.85) for non-emergency vehicles (Class 0). For emergency vehicles (Class 1), precision is fairly strong (0.75), but recall is higher (0.70), indicating emergency vehicles are accurately classified. The confusion matrix reveals 92 true positives, 30 false positives, 168 true negatives, and 40 false negatives, highlighting misclassification between the two classes.

Other models were tuned but there was no significant improvement in classifying the emergency vehicles.

DISCUSSION

The CNN model developed in this study achieved 83% accuracy in classifying emergency vehicles, similar to approaches in the literature. Alaoui et al. (2023) used pre-trained CNNs for vehicle classification, likely achieving comparable results by leveraging transfer learning. Deepajothi et al. (2021) applied CNNs to traffic management, which, while focused on optimization rather than classification, demonstrates the broader potential of CNNs in transportation. The 83% accuracy is promising but can be improved further with techniques like transfer learning or architectural adjustments.

Conclusion

The potential of this model for real-world applications such as traffic management systems could be robust. Limitations such as slight class imbalance and a small dataset impacted results. Future work would be to incorporate video traffic data and train the models for a higher number of epochs for improved generalization.

Component Three

Critical Evaluation of Ethical Challenges in Healthcare Artificial Intelligence Systems

Abstract

Abstract:

The integration of artificial intelligence (AI) in healthcare has transformed patient care and diagnosis, yet it raises significant ethical concerns regarding transparency, fairness, and accountability. This evaluation explores the ethical challenges of implementing AI in healthcare through a systematic review of peer-reviewed literature. Key issues, including transparency in AI systems and the potential for bias, are examined alongside existing ethical frameworks. The study identifies innovations like Explainable AI (XAI) to improve trust and transparency and recommends measures to ensure fairness in data collection and algorithm development. The report concludes with suggestions for enhancing the ethical deployment of AI in healthcare, emphasizing the need for improved legal and ethical guidelines.

Keywords: Artificial intelligence ethics, transparency, fairness and bias, healthcare
Word Count: 108

Introduction

The application of artificial intelligence in healthcare has revolutionized patient care, medical diagnosis, and medical research (Rigby, 2019). However, the potential of artificial intelligence calls for attention to the ethical dilemma of ensuring that these systems are transparent, trustworthy, fair, and socially responsible. This evaluation will critically appraise the ethical challenges in implementing AI within the Healthcare sector. Through a review of peer-reviewed journals, this essay will explore the technical challenges, particularly transparency in implementing AI solutions, an evaluation of the ethical framework that exists, and propose innovations to enhance the ethical deployment of artificial intelligence in healthcare.

According to the Oxford Dictionary, ethics refers to a set of moral principles that govern an individual's behavior or the conducting of an activity. Tzafestas (2018) cited in Khosravi et al (2024) submitted that ethics is a branch of philosophy that provides a standard for determining what is deemed right or wrong.

Methodology

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework was adopted in this study and aimed to discuss the ethical challenges involved in the deployment of AI systems in Healthcare. Peer-reviewed journals were sourced from academic databases such as Springer Link, Google Scholar, and PubMed using the keyword

‘Ethical frameworks in AI and healthcare’. The results generated were further refined to align with the objective of this study.

Technical Challenges in Implementing Transparency into AI Systems

Khosravi et al (2024) conducted a systematic review of existing systematic reviews using the PRISMA framework aimed at investigating the ethical challenges involved in the application of AI in healthcare service delivery. Transparency in AI refers to the capacity of technologies to deliver clear and comprehensible explanations of their inputs, processes, and outputs (Prakash et al., 2022). Transparency is a key theme in the design and implementation of AI systems in healthcare. The concern is that an AI system that will be deployed in healthcare must be able to provide reasonable justifications on what it does, how it works, and the potential benefits and challenges that arise in its application to solve real-world problems. However, challenges to transparency in AI systems continue to exist. Linardatos et al (2021), cited in Kiseleva et al (2022) submitted that the black-box component of some machine learning models such as deep learning, where the relationship between the input data and the output is non-linear and highly complex, becomes a challenge attempting to explain in detail the operation that has taken place to arrive at predictions. For example, convolutional neural networks are widely used in cancer detection using mammograms. Similarly, machine learning algorithms are deployed in the detection of Autism Spectrum Disorder (ASD) by analyzing large datasets and identifying patterns and markers that are indicative of the disease, aiding diagnosis and treatment (Nasir et al., 2024). According to Khrosavi et al., (2024), challenges such as the opacity and unpredictability of complex AI systems pose a barrier to transparency. The authors submitted that transparency can be achieved through a set of closely related measures such as explainability and accountability, communication, record-keeping, data governance, and management.

Ethical Framework Evaluation in AI Systems for Healthcare

Existing ethical frameworks that guide the use of AI systems in healthcare attempt to ensure fairness, accountability, transparency, and patient safety. This section analyzes the strengths and limitations of existing frameworks discussed in peer-reviewed articles and evaluates how they address real-world challenges.

Trust and Transparency

The proposed AI Act by the European Commission is intended to cover mainly what is described as ‘high risk’ AI systems. In other words, systems shouldered with the responsibility of making life-or-death decisions should be trusted (Kiseleva et al., 2022). AI systems in healthcare are generally classified as high-risk. One of the strengths of this framework is that it requires the users of AI systems to be able to interpret the AI's system output and apply it appropriately. The black-box component of artificial intelligence renders decision-making obscure (Prakash et al., 2022).

A limitation of this approach is that there is generally a lack of interpretability as it pertains to the complex models used in developing AI systems. Nevertheless, different approaches have been proposed to achieve explainability in AI as submitted by Lin et al (2021).

Fairness and Bias

Fairness and Bias are also of major concern because of the potential damage and negative consequences that could result from negligence. One of the strengths of fairness in the application of AI systems in healthcare is the representation of minority groups and inclusion the allocation of resources. Although it is understood that bias is inevitable and as such may be embedded in algorithmic solutions proposed to problems in healthcare which can exacerbate healthcare disparities among minority groups. Obermeyer et al (2019) study highlights the gross disparity that exists in healthcare systems in the United States based on AI. The algorithm was revealed to be racially biased by focusing on spending as an indicator of the allocation of healthcare resources. Karimian et al (2022) submitted that bias in the development phase of an algorithm has the potential to lead to discrimination, underrepresentation of minority groups, and lack of fair provision of care.

Furthermore, dataset limitations pose a significant challenge in developing algorithmic solutions. The process of data gathering could influence the use of artificial intelligence models to generalize to a wider population (Khorsavi et al., 2024; Nasir et al., 2024).

Privacy

The proliferation of AI solutions in healthcare necessitates the protection of patient data (Murdoch, 2021). The General Data Protection Regulation (GDPR) by the European Union provides a legal framework that protects the data and privacy of individuals which is a strength. However, corporations that utilize patient health information are not entirely transparent about its usage.

Innovation and Solutions

One of the solutions that could improve trust and transparency is the Explainable Artificial Intelligence (XAI) technique as submitted by Nasir et al (2021). Adadi and Berrada (2020) cited in Nasir et al (2021) opined that XAI aims to improve the transparency and interpretability of AI models, by providing insights into the decision-making process and enabling healthcare service providers to understand the reasoning behind AI-generated solutions.

To adequately address bias in the development of algorithmic solutions, policymakers, stakeholders, developers, and end-users must set out guidelines that ensure the inclusion of under-represented groups in the process of data gathering, and model development.

Synthesis of Peer-Reviewed Articles

All the studies emphasized the importance of developing ethical principles and guidelines to support the use of AI in healthcare, as existing legal codes and ethical frameworks are not adequately aligned with current or future AI applications in the field. Given AI's susceptibility to errors, patients tend to favor compassionate human care over-reliance on artificial systems. The protection of patient data was also discussed concisely.

Conclusion

In this report, several peer-reviewed journals were critically evaluated on the adoption of AI in the healthcare industry. The ethical principles guiding the use of AI systems in healthcare were examined and solutions to the challenges that exist were proposed.

List of Peer-Reviewed Articles

Karimian, G., Petelos, E. and Evers, S.M., 2022. *The ethical issues of the application of artificial intelligence in healthcare: a systematic scoping review*. AI and Ethics, 2(4), pp.539-551.

Khosravi, M., Zare, Z., Mojtabaeian, S.M. and Izadi, R., 2024. *Ethical challenges of using artificial intelligence in healthcare delivery: a thematic analysis of a systematic review of reviews*. Journal of Public Health, pp.1-11.

Kiseleva, A., Kotzinos, D. and De Hert, P., 2022. *Transparency of AI in healthcare as a multilayered system of accountabilities: between legal requirements and technical limitations*. Frontiers in Artificial Intelligence, 5, p.879603.

Murdoch, B., 2021. *Privacy and artificial intelligence: challenges for protecting health information in a new era*. BMC Medical Ethics, 22, pp.1-5.

Nasir, S., Khan, R.A. and Bai, S., 2024. *Ethical framework for harnessing the power of AI in healthcare and beyond*. IEEE Access, 12, pp.31014-31035.

REFERENCES

Adadi, A. and Berrada, M., 2020. *Explainable AI for healthcare: From black box to interpretable models*. In: *Embedded Systems and Artificial Intelligence*. Singapore: Springer, vol. 1076. Available at: https://doi.org/10.1007/978-981-15-0947-6_31.

Alaoui, A.O., El Bahi, O., Fethi, M.R., Farhaoui, O., El Allaoui, A. and Farhaoui, Y., 2023. *Pre-trained CNNs: Evaluating emergency vehicle image classification*. Data and Metadata, 2, pp.153-153.

Deepajothi, S., Rajan, D.P., Karthikeyan, P. and Velliangiri, S., 2021. *Intelligent traffic management for emergency vehicles using convolutional neural network*. In 2021 7th International Conference on Advanced Computing and Communication Systems *(ICACCS)*, Vol. 1, pp.853-857. IEEE.

Goodfellow, I., Bengio, Y. and Courville, A., 2016. *Deep learning*. Cambridge: MIT Press.

Huang, W., 2023. *Research on the prediction of the sales of electronic games*. Highlights in Business, Economics and Management, 21, pp.13-20.

Jahan, N., Islam, S. and Foysal, M.F.A., 2020. *Real-time vehicle classification using CNN*. In 2020 11th International Conference on Computing, Communication and Networking Technologies (ICCCNT), pp.1-6. IEEE

Li, J., Zheng, Y., Hu, H., Lu, J. and Zhan, C., 2021. *Predicting video game sales based on machine learning and hybrid feature selection method*. In: *2021 16th International Conference on Intelligent Systems and Knowledge Engineering (ISKE)*, pp.497-502. IEEE.

Linardatos, P., Papastefanopoulos, V. and Kotsiantis, S., 2020. *Explainable AI: A review of machine learning interpretability methods*. *Entropy*, 23(1), p.18.

Lin, S., Lee, W.-C. and Celik, Z.B., 2021. *What do you see: Evaluation of explainable artificial intelligence (XAI) interpretability through neural backdoors*. In: Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery and Data Mining, pp.1027-1035.

Nasir, S., Khan, R.A. and Bai, S., 2024. *Ethical framework for harnessing the power of AI in healthcare and beyond*. IEEE Access, 12, pp.31014-31035.

Obermeyer, Z., Powers, B., Vogeli, C. and Mullainathan, S., 2019. *Dissecting racial bias in an algorithm used to manage the health of populations*. Science, 366(6464), pp.447-453.

Prakash, S., Balaji, J.N., Joshi, A. and Surapaneni, K.M., 2022. *Ethical conundrums in the application of artificial intelligence (AI) in healthcare*—a scoping review of reviews. *Journal of Personalized Medicine*, 12(11), p.1914.

Rigby, M.J., 2019. Ethical dimensions of using artificial intelligence in health care. *AMA Journal of Ethics*, 21(2), pp.121-124.

Tzafestas, S.G., 2018. *Ethics and law in the Internet of Things world*. *Smart Cities*, 1(1), pp.98-120.

Vishwakarma, S. and Kumari, R., 2024. *Video game sales prediction model using regression model.* Journal of Computational and Applied Mathematics.

World Economic Forum, 2016. *The number of cars worldwide is set to double by 2040*. *https://www.weforum.org/stories/2016/04/the-number-of-cars-worldwide-is-set-to-double-by-2040/#:~:text=The%20global%20number%20of%20cars,trillion%20in%20the%20same%20period*. [Accessed 29 November 2024].