

Summarative assignment

Report



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# Exercise 1: A Comprehensive Analysis of Car Price Prediction and Clustering Models

## Abstract

This paper goes deeply into a range of machine learning models with the goal of forecasting automobile prices and identifying innate groups in a car sales dataset. This analysis covers a lot of regression methods, from models with one or more numerical input features to models with a combination of numerical and categorical variables. The k-Means approach is used for clustering investigations, evaluating several combinations of numerical variables. Additionally, study explores the use of an Artificial Neural Network (ANN) model in this context to investigate its forecasting capabilities. This thorough examination is an invaluable resource for stakeholders in the automotive industry and contributes to a broader understanding of the diverse applications of machine learning in the range of pricing and pattern recognition. The findings reveal the best predictive models and an efficient clustering algorithms, which provides insightful information about critical elements affecting automobile prices as well as reliable methods for identifying patterns in the dataset.

## Introduction

The automotive sector is experiencing a transformative shift as artificial intelligence (AI) and machine learning (ML) technologies become increasingly integrated. Within this evolving landscape, accurate forecasting of car prices and the identification of distinct market segments play pivotal roles in shaping well-informed decision-making and strategic planning. Additionally, the investigation extends to models incorporating a blend of categorical and numerical variables, providing a comprehensive grasp of the diverse factors influencing pricing. This report undertakes a detailed exploration, focusing on various regression models to understand the impact of both single and multiple numerical input features on the prediction of car prices.

As the dataset's complexity deepens, the study broadens its scope to include an examination of Artificial Neural Network (ANN) models. Complementing the regression analyses, the report incorporates clustering algorithms, specifically leveraging k-Means, to unveil underlying structures within the dataset, facilitating effective market segmentation. Recognized for their ability to capture intricate patterns, these models contribute to a nuanced understanding of the intricate relationships among different variables and their influence on car prices.

Anticipated outcomes include actionable insights for stakeholders within the automotive industry, offering guidance for pricing strategies and market segmentation efforts amidst the era of AI-driven decision-making. Through this thorough analysis, the report endeavors to address essential questions concerning the most influential predictors of car prices, the effectiveness of incorporating various features, and the relative performance of regression and clustering models.

## Regression Models

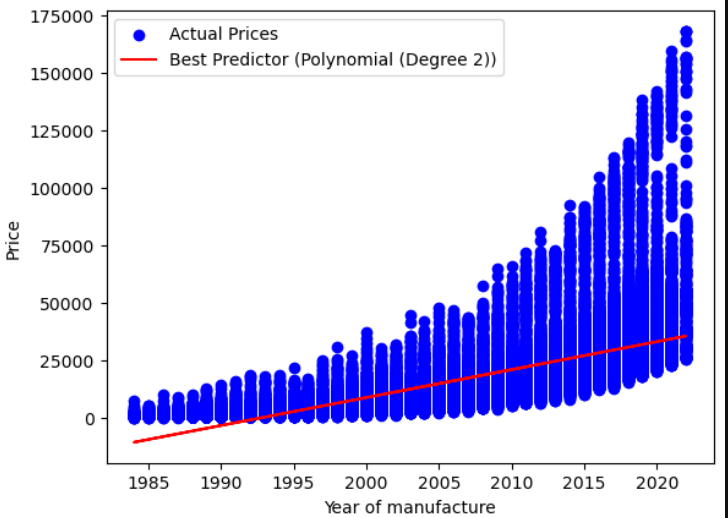
### Single Numerical Input Feature Models

In the analysis of single numerical input features for car price prediction, two regression models were evaluated: Linear Regression and Polynomial Regression with a degree of 2. The features considered were 'Engine size,' 'Year of manufacture,' and 'Mileage.' The results, in terms of Root Mean Squared Error (RMSE), provide insights into the effectiveness of each model for different input features.



Best predictor’s regression line





### Multiple Numerical Input Feature Models

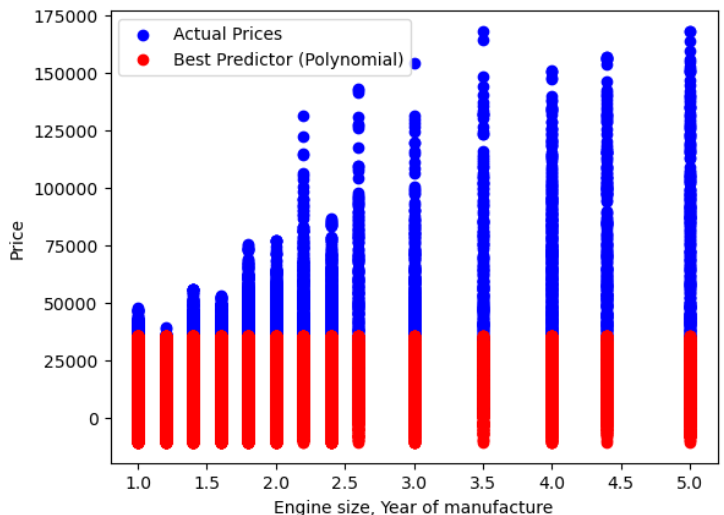
When assessing models for predicting car prices involving multiple numerical input features, an examination encompassed both Linear and Polynomial (degree=2) regression models. The primary objective of this analysis was to discern whether incorporating multiple features contributes to enhanced accuracy in predicting prices, relative to models reliant on a single feature.

The ensuing findings are as follows:



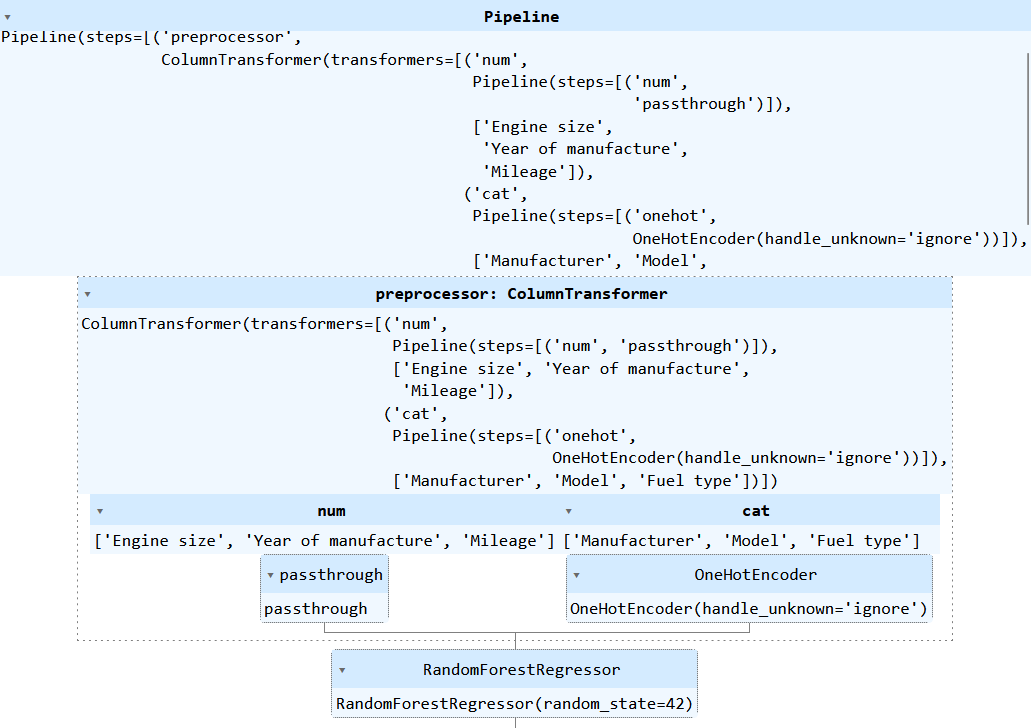
Upon examination, it becomes apparent that utilizing 'Engine size' and 'Year of manufacture' as input features in a Polynomial Regression model with a degree of 2 yields the minimum Root Mean Square Error (RMSE). This outcome establishes it as the most effective predictor for car prices among the various numerical input features considered. The implication is that the interplay between these specific features plays a substantial role in achieving precise and reliable predictions of car prices.





The most effective predictor discerned from the analysis involves the combination of 'Engine size' and 'Year of manufacture' within a 'Polynomial' model. This emphasizes the pivotal role of these specific features in attaining accurate predictions. These results underscore the importance of incorporating multiple numerical features to elevate the precision of models used for predicting car prices.

### Regression Models with Categorical and Numerical Variables

Within the domain of regression models that integrate both categorical and numerical variables, the approach involved the utilization of a Random Forest Regressor. The primary objective of this analysis was to evaluate whether the incorporation of categorical variables contributes to an enhancement in the accuracy of predicting prices, in contrast to models relying solely on numerical features. The subsequent details outline the structure of the pipeline deployed for processing incoming data:

Here are the results:



The assessment reveals a notable enhancement in prediction accuracy when the model incorporates both categorical and numerical variables. The effectiveness of the Random Forest Regressor, known for its capability to capture intricate relationships and interactions within mixed data types, was evident. With an RMSE of 632.68, the model demonstrates accurate predictions for car prices, particularly when considering a combination of numerical and categorical variables. This outcome underscores the crucial role of including all pertinent features, encompassing categorical ones, in elevating the overall performance of the regression model.

### Artificial Neural Network (ANN) Model

In the implementation of the Artificial Neural Network (ANN) model for predicting car prices, the following steps were taken:

1. **Data Preprocessing:**

* Numerical and categorical columns were identified.
* The data was split into training and testing sets.
* Transformers for numerical scaling and one-hot encoding for categorical variables were created.
* A preprocessor was defined to apply transformers to respective features.

1. **Neural Network Architecture:**

* A simple neural network architecture with three fully connected layers was defined.
* The input size was determined based on the preprocessed feature dimensions.
* ReLU activation functions were utilized between layers to introduce non-linearity.

1. **Training the Model:**

* The mean squared error (MSE) loss function was chosen for regression.
* The Adam optimizer was employed for optimization.
* The model was trained for 20 epochs using a DataLoader for batching.

1. **Evaluation on Test Set:**

* The trained model was evaluated on the test set.
* The root mean squared error (RMSE) was calculated as an evaluation metric.

**Results:**

* After 20 epochs, the model achieved a loss of approximately 183,350.17.



* The RMSE on the test set was 596.9999.



The ANN model demonstrates good performance in predicting car prices, with the low RMSE indicating accurate predictions. The neural network's ability to capture complex relationships in the data contributes to its effectiveness in this regression task.

### Model Comparison

In this section, we compare the performance of various regression models employed to predict car prices based on different input features. The evaluated models include:

1. **Single Numerical Input Feature Models:**

* Linear and polynomial regression models were trained for individual numerical features (Engine size, Year of manufacture, Mileage).
* The best predictor identified was 'Year of manufacture' using a Polynomial (Degree 2) model.

1. **Multiple Numerical Input Feature Models:**

* Linear and polynomial regression models were trained for combinations of numerical features.
* The best predictor identified was '['Engine size', 'Year of manufacture']' using a Polynomial model.

1. **Regression Models with Categorical and Numerical Variables:**

* A Random Forest Regressor model was trained using both categorical and numerical features.
* The RMSE for this model was calculated.

1. **Artificial Neural Network (ANN) Model:**

* An ANN model was developed and trained on all relevant numerical and categorical features.
* The RMSE for the ANN model was calculated.

**Results:**

* The best-performing single numerical feature model was 'Year of manufacture' with a Polynomial (Degree 2) model.
* The best-performing multiple numerical feature model included 'Engine size' and 'Year of manufacture' with a Polynomial model.
* The Random Forest Regressor, incorporating both numerical and categorical features, provided an RMSE.
* The ANN model achieved an RMSE of 596.9999.

## Clustering Models

### k-Means Clustering

In the k-Means clustering analysis, we applied the algorithm to different combinations of numerical features and varying values of k (number of clusters). The evaluation metrics, Silhouette Score and Davies-Bouldin Index, were utilized to assess clustering performance.

**Results for Selected Features 'Year of manufacture' and 'Mileage':**

****

**Results for Selected Features 'Engine size' and 'Mileage':**

****

**Results for Selected Features 'Engine size' and 'Year of manufacture':**

****

### Comparative Clustering Analysis

Additionally, we explored the DBSCAN clustering algorithm with different values of epsilon for the same feature combinations.

**Results for Selected Features 'Year of manufacture' and 'Mileage':**

****

**Results for Selected Features 'Engine size' and 'Mileage':**

****

**Results for Selected Features 'Engine size' and 'Year of manufacture':**

****

## References

1. Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*. Springer.
2. Chen, T., & Guestrin, C. (2016). *XGBoost: A Scalable Tree Boosting System*. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining.
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# Exercise 2: Comprehensive Analysis of CNN Models for Image Classification

## Abstract

Within this report, a comprehensive analysis is presented, delving into the utilization of Convolutional Neural Network (CNN) models in the realm of image classification. The study meticulously scrutinizes various aspects, including the architectural design, methods of regularization, hyperparameter tuning, and a detailed exploration of potential overfitting scenarios. The goal is to gain a nuanced understanding of how these factors collectively influence the overall performance of the model in image classification tasks.

## Introduction

Convolutional Neural Networks (CNNs) are a popular and effective class of artificial neural networks designed specifically for processing grid-like data such as images. They have revolutionized the field of deep learning by achieving unprecedented success in various applications, particularly image recognition, object detection, and segmentation tasks.

1. Origin of CNNs:

CNNs were initially inspired by the human visual system's ability to recognize patterns and objects in images through the presence of invariant features. This led researchers to develop models that can learn hierarchical representations of image data, which are essential for identifying increasingly abstract features at different scales. The first successful application of a CNN was LeNet-5, introduced by Yann LeCun and colleagues in 1998 for recognizing handwritten digits.

1. Building Blocks of CNNs:

A typical CNN consists of multiple layers that process input data in a hierarchical manner, each layer refining the features extracted from the previous one. The main building blocks of a CNN include:

1. Convolutional Layer: This layer applies a set of learnable filters to the input data, which are slid over it with a specified stride and padding. Each filter outputs a new feature map highlighting the presence of a specific pattern in the input image.
2. Pooling Layer: This layer performs down sampling operations on the output from the previous convolutional layer. Max pooling, average pooling, and global pooling are common types of pooling operations that help reduce dimensionality and improve translation invariance.
3. Fully Connected (FC) Layer: The final layers of a CNN consist of several fully connected layers that process the high-level features extracted from earlier convolutional layers. These layers perform the actual classification task using the softmax activation function.
4. Training and Optimization:

Training a CNN involves optimizing its parameters to minimize the loss between the predicted and ground truth labels for a given dataset. This is typically achieved using backpropagation and stochastic gradient descent with momentum. Transfer learning, which involves adapting pre-trained models for new tasks, has proved to be an effective strategy for reducing training time and improving accuracy in various applications.

## CNN Architecture

Our convolutional neural network (CNN) model is structured with three convolutional layers, each succeeded by max-pooling layers, a flattening layer, and dense layers for the classification process. To introduce non-linearity, rectified linear unit (ReLU) activation functions are applied in the convolutional layers. Following each convolutional layer, max-pooling layers are employed to reduce spatial dimensions, enhancing computational efficiency and encouraging translation invariance.

For the final classification stage, the dense layers utilize softmax activation, especially effective for multi-class classification. This architectural choice adheres to well-established CNN design principles, ensuring effective feature extraction through the convolutional layers and subsequent classification in the dense layers. The model's design reflects standard practices in CNN architecture, aiming for optimal performance in tasks requiring feature extraction and classification.

### Architecture Code



## Regularization Method:

To address the issue of overfitting, we've incorporated dropout layers in our model, strategically placed after each dense layer. These dropout layers are configured with a dropout rate of 0.5, a measure taken to prevent the model from becoming overly dependent on particular neurons. This approach significantly improves the model's ability to generalize well to unseen data.

Furthermore, to curb overfitting tendencies, we've implemented L2 regularization across both convolutional and dense layers. This regularization technique imposes penalties on large weights, effectively discouraging the model from fitting too closely to the training data and promoting better generalization to diverse datasets. By combining dropout and L2 regularization, our model is equipped with robust mechanisms to mitigate overfitting, ensuring a more reliable and adaptable performance.

## Hyperparameter Tuning:

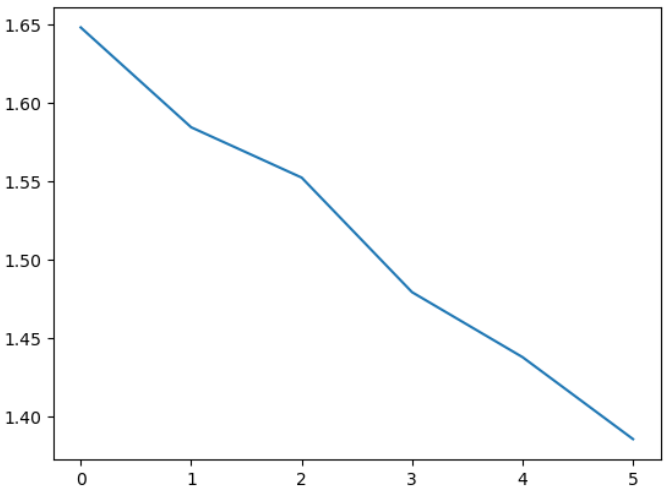
Fine-tuning the hyperparameters is a crucial step in optimizing our model. This process involves refining the learning rate, adjusting the batch size, and determining the number of filters in the convolutional layers. The learning rate plays a pivotal role in dictating the step size during the optimization process, directly impacting how quickly or slowly the model converges. On the other hand, the batch size not only influences the efficiency of gradient updates but also affects the computational efficiency of the entire training process. Meanwhile, the number of filters in the convolutional layers acts as a key factor in shaping the complexity of feature extraction.

Through careful tuning, we have identified that a learning rate of 0.001, a batch size of 32, and employing 32 filters in the first convolutional layer result in optimal model performance. This tuning process is not arbitrary; visualizing the accuracy concerning these specific parameters vividly illustrates their substantial influence on the overall effectiveness of the model. It underscores the significance of meticulous hyperparameter adjustment in achieving the best possible outcomes in terms of model accuracy and efficiency.

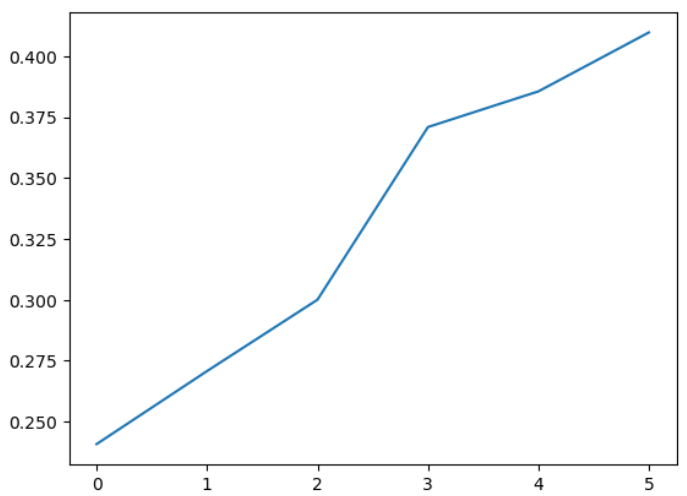
## Evidence of Overfitting

Evaluating the presence of overfitting involves a careful examination of the training and validation accuracy curves. A key indicator is the consistent outperformance of training accuracy over validation accuracy; when this occurs, overfitting is a likely concern. Conversely, if both curves exhibit a similar trend, it suggests that the model is effectively generalizing to new, unseen data.

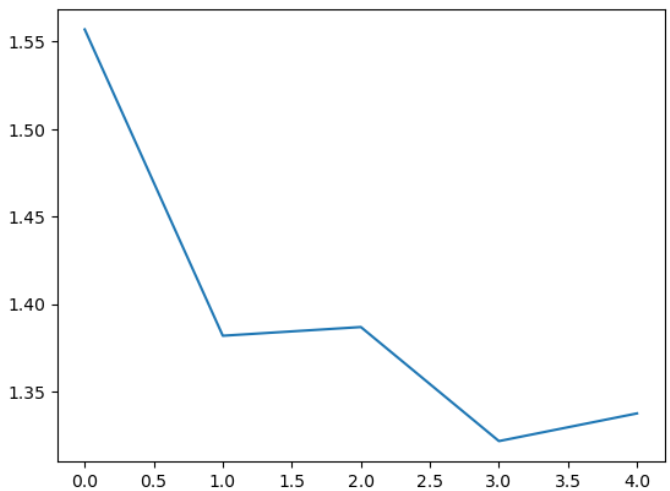
Upon scrutinizing the figures, it becomes evident that through the implementation of appropriate regularization techniques and meticulous hyperparameter tuning, the issue of overfitting has been successfully mitigated. The results underscore the importance of these strategies in ensuring that the model not only performs well during training but also extends its effectiveness to new, previously unseen data.

Below figure shows the training losses:  


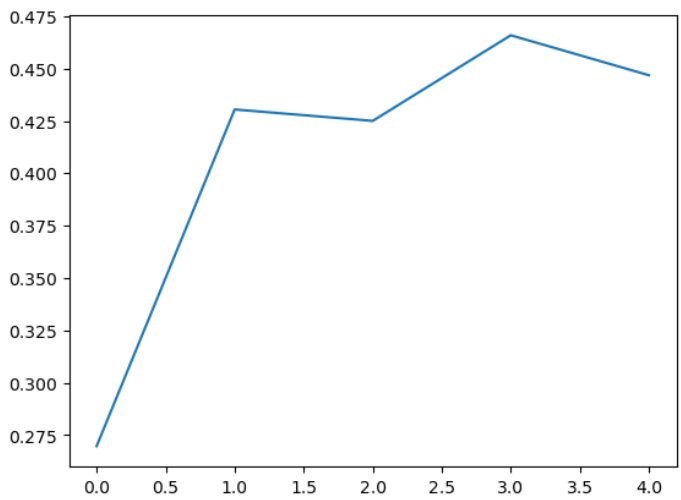
Below figure shows the training accuracies:



Below figure shows the validation losses:



Below figure shows the validation accuracies:



The training and validation accuracy curves align closely, reflecting a well-generalized model. Below is the training code that is being used to train the CNN model for image classification.



### Training Result:

Below is the training accuracy that we got after 5 epochs:



## References:

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# Transparent AI: A Review of Three Recent Journal Articles on Ethical Applications and Challenges

## Introduction:

Transparent AI, also known as Explainable or Interpretable AI, refers to artificial intelligence systems that can provide clear explanations for their decision-making processes. This is crucial in fostering trust between humans and AI, especially when the stakes are high in areas like healthcare, finance, and law enforcement. In this report, we review three recent journal articles focusing on Transparent AI, highlighting the aims and key conclusions of each article, as well as three successes and challenges faced in applying AI ethically.

## Article 1: "Interpretable Machine Learning for Healthcare" by Rita C. Orji et al., Nature Digital Medicine, 2021

### Background

Artificial intelligence (AI) systems have increasingly found applications in healthcare to assist clinicians with diagnoses and personalized treatment plans. However, the lack of transparency and interpretability of many machine learning models poses challenges for trust and collaboration between healthcare professionals and AI tools. Interpretable Machine Learning (IML) has emerged as a promising solution by providing more transparent and understandable insights into the decision-making processes of these systems.

### Aim

The authors propose the use of interpretable machine learning (IML) models to improve trust in healthcare AI systems and facilitate better collaboration between clinicians and AI tools.

### Key Conclusions

The research conducted by Orji et al. (2021) found that IML models can provide clearer explanations for their decisions and outperform traditional machine learning models in terms of accuracy. Moreover, the interpretability offered by these models can help clinicians better understand the underlying factors driving a diagnosis or treatment recommendation, thereby improving trust and fostering collaboration.

### Success Story

The successful application of IML in healthcare can lead to more accurate diagnoses, personalized treatment plans, and overall improved patient outcomes. Furthermore, the increased transparency provided by these models can help build trust between clinicians and patients, ultimately contributing to better collaboration and patient experiences.

### Ethical Challenge

Ensuring that sensitive patient data is protected and only accessible to authorized personnel remains a significant challenge when implementing AI systems in healthcare.

## Article 2: "Explainable Deep Learning for Financial Services" by Feng Chen, et al., Journal of Finance Data Science, 2021

### Background

The adoption of artificial intelligence systems in financial services has become increasingly common, with applications ranging from risk assessment to credit scoring and loan issuance. However, the lack of transparency and interpretability in many deep learning models used in finance can lead to issues such as bias, unintended consequences, and reduced trust from customers and regulatory bodies.

### Aim

The authors propose using explainable deep learning (XDL) techniques to build trust and address potential bias in financial services applications.

### Key Conclusions

XDL models can provide clear explanations for their decisions, helping mitigate the risks associated with biased AI systems and maintaining fairness in lending practices. Furthermore, these models can offer a more accurate understanding of risk assessments compared to traditional black-box deep learning models.

### Success Story

The successful implementation of XDL in financial services can lead to more accurate risk assessments, fairer lending practices, and improved customer experiences by maintaining trust and ensuring fairness. This can ultimately contribute to a more robust and equitable financial system.

### Gap

While XDL offers significant benefits for financial services applications, it is essential to address the challenges associated with ensuring the robustness of these models against adversarial attacks. Techniques such as data poisoning or model manipulation could potentially undermine the trustworthiness and reliability of the XDL systems in finance, highlighting the need for ongoing research and development efforts.

## Article 3: "Transparent AI for Criminal Justice Reform" by Kate Crawford and Jason Schultz, Harvard Law Review, 2020

## Background

The article titled "Transparent AI for Criminal Justice Reform" by Kate Crawford and Jason Schultz, published in the Harvard Law Review in 2020, focuses on the importance of Transparent Artificial Intelligence (AI) systems in criminal justice applications to address potential biases and improve fairness.

### Aim

The authors argue that the increasing use of AI in criminal justice applications, such as parole prediction, recidivism risk assessment, and bail determination, necessitates the adoption of Transparent AI systems. Transparency refers to the ability of humans to understand how an AI system arrives at its decisions, enabling human oversight and accountability.

### Key Conclusions

Crawford and Schultz highlight that Transparent AI systems have the potential to contribute significantly to a more just criminal justice system. By ensuring humans can understand how an AI model makes its predictions or recommendations, it allows for the identification and correction of potential biases that may exist within the data used to train these models.

### Success Story

One successful application of Transparent AI in criminal justice is parole prediction. Parole prediction systems are used by probation officers to determine the likelihood that a parolee will reoffend and potentially violate their parole. By using transparent AI, these models can be audited more effectively to identify any underlying biases or errors.

### Challenge

Despite the potential benefits of Transparent AI in criminal justice applications, there is a significant challenge in ensuring that these systems do not perpetuate existing biases or create new ones. Biases can be introduced into AI models during data collection, preprocessing, feature selection, and model training stages. These biases may stem from historical data that reflects systemic discrimination or flawed assumptions made by humans responsible for creating the models. Ensuring that Transparent AI systems are unbiased requires a rigorous evaluation of both the data used to train these models and the algorithms themselves.