Predicting Customer Spending Behaviour in Streaming Services (Component 1)

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Understanding Artificial Intelligence (771763_B24_T2).

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Abstract

This report applies supervised and unsupervised machine learning techniques to model customer behaviour in the streaming industry. The goal was to predict monthly spending, identify customer churn, and extract behavioural segments. Regression analysis using linear regression, random forests, and artificial neural networks (ANNs) was conducted to predict monthly spend. The best performing model was an ANN (Model V6), achieving a root mean squared error (RMSE) of 3.22 and an R^2 score of 0.8854, indicating a strong fit. For churn prediction, the Random Forest Classifier achieved the highest performance with 98.2% accuracy, an F1-score of 0.9815, and an AUC of 0.9941, aided by SMOTE to handle class imbalance. In clustering analysis, k-means produced better-defined segments (average Silhouette Score: 0.52) than DBSCAN (0.37). When clustering individual features, Satisfaction_Score and Discount_Offered achieved the highest silhouette scores (0.7736 and 0.7650, respectively). Overall, ensemble and neural models demonstrated high predictive accuracy and offer practical applications in customer retention and personalised marketing.

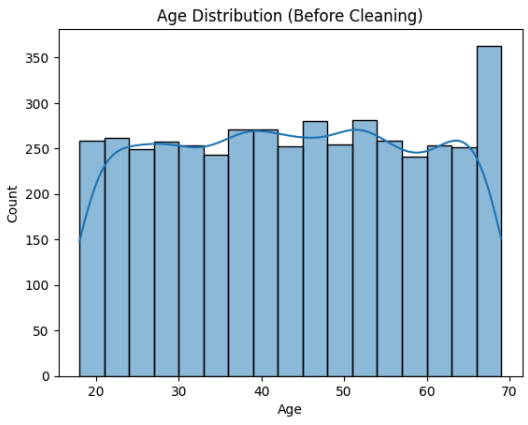
Introduction

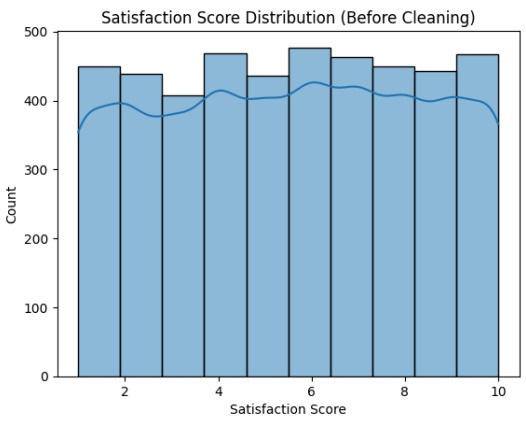
Predicting customer behaviour is vital for subscription services seeking to reduce churn and personalise offers (Ngai et al., 2009). Modern machine learning (ML) approaches can uncover non-obvious behavioural patterns, enabling smarter segmentation and predictive targeting (Kotu and Deshpande, 2019). This report investigates spending prediction through regression, churn detection using classification, and behavioural segmentation with clustering. The dataset includes demographic, behavioural, and transactional features such as age, satisfaction score, discount offered, and subscription length. Models compared include random forests, SVMs, artificial neural networks, and k-means clustering. Performance is evaluated using standard metrics such as RMSE, F1-score, and silhouette score. Insights are drawn regarding the most effective models and predictors for future deployment.

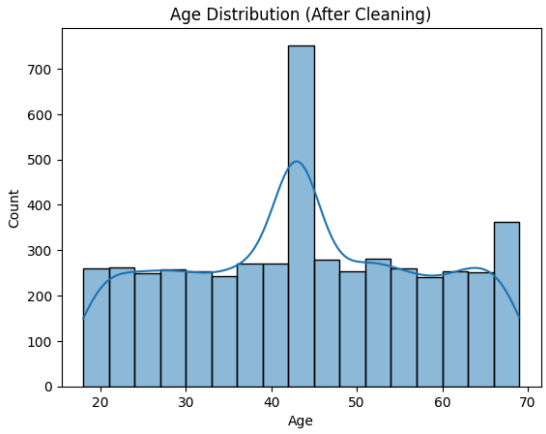
Methodology

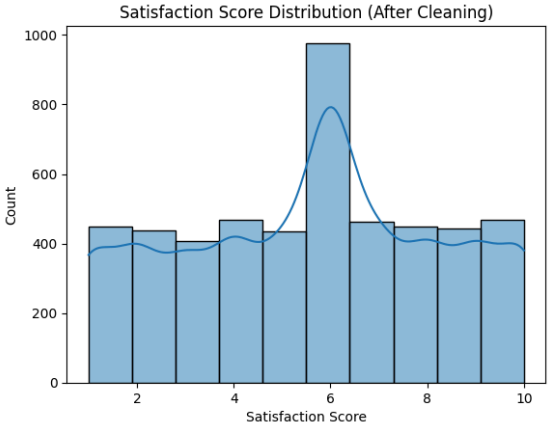
Data Preprocessing

Missing values in Age and Satisfaction_Score were handled using median imputation to reduce skewness (Han et al., 2011). Categorical variables like Region and Payment_Method were one-hot encoded (Kotu and Deshpande, 2019), and numerical features were standardised for compatibility with models like ANN and k-means (Zhang et al., 2019). Class imbalance in churn data was addressed using SMOTE, which generates synthetic samples for the minority class (Chawla et al., 2002). The data were divided into training and testing subsets in an 80:20 split, ensuring each subset maintained the original class distribution through stratified sampling.





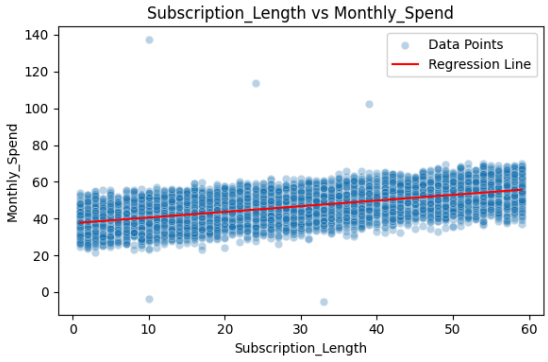




Regression Modeling

(a) Simple Regression

Polynomial regression was applied to individual numerical features to assess their relationship with monthly spending. Satisfaction_Score was the most predictive variable, with an R^2 of 0.5345 and RMSE of 6.49, suggesting that more satisfied users tended to spend more (Kumar et al., 2006). Subscription_Length followed with moderate predictive value (R^2 = 0.2820), while Discount_Offered had weak correlation (R^2 = 0.0454). Features like Support_Tickets_Raised and Last_Activity showed negligible influence on spending.



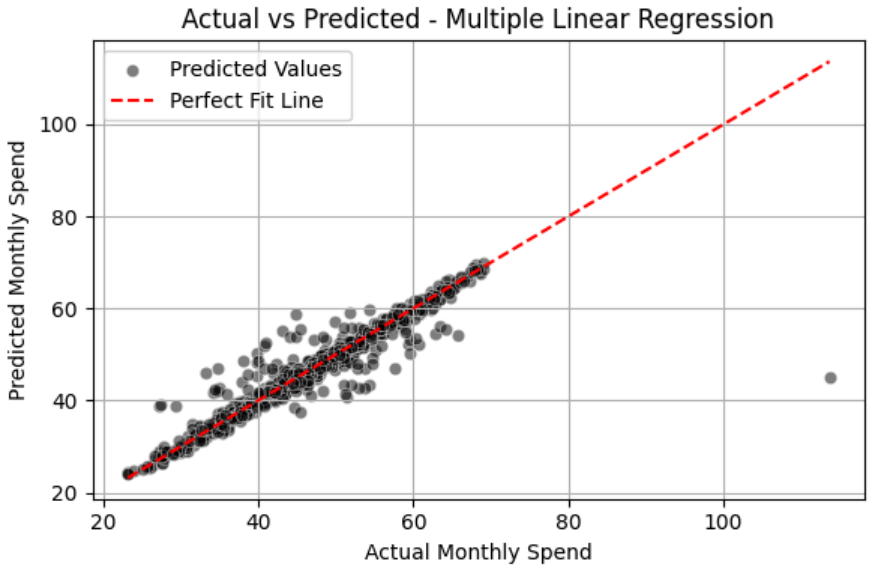
(b) Multivariable Regression

A multiple linear regression model using all numerical features produced strong results, with an R^2 of 0.8861 and RMSE of 3.21. This indicates that the combined features explained a

significant proportion of the variance in monthly spending. Compared to individual predictors, the multivariable model captured broader patterns more effectively, benefiting from the linear contributions of variables like Satisfaction_Score and Subscription_Length.

(c) Regression with Categorical Variables

The model leveraged a random forest regressor using both numerical variables and one-hot encoded categorical data., achieving an R^2 of 0.8656 and RMSE of 3.49. Though slightly less accurate than linear and ANN models, it handled non-linear interactions effectively. Key predictors remained Satisfaction_Score and Subscription_Length, while categorical features had limited impact.



(d) Artificial Neural Network (ANN)

An artificial neural network (ANN) trained on standardised inputs achieved an R^2 of 0.8854 and RMSE of 3.22, matching the performance of linear regression. The model captured non-linear patterns effectively, and loss curves showed stable learning with no overfitting across early epochs. This confirms its suitability for complex spending prediction tasks (Goodfellow et al., 2016).

Classification: Churn Prediction

Churn prediction was carried out using Logistic Regression, Support Vector Machine (SVM), K-Nearest Neighbours (KNN), and Random Forest classifiers. SMOTE was used to address class imbalance prior to training. Input features included standardised numerical data and one-hot encoded categorical variables such as Region and Payment_Method.

Among all models, the Random Forest Classifier achieved the best performance, with 98.2% accuracy, F1-score of 0.9815, and AUC-ROC of 0.9941, confirming its strong generalisation and sensitivity to churn cases (Breiman, 2001). SVM and KNN also performed well, but with lower F1-scores of 0.9435 and 0.8729, respectively. Feature importance analysis highlighted Satisfaction_Score, Subscription_Length, and Discount_Offered as the most influential predictors, rather than spending or time-based features.

Clustering: Customer Segmentation

Clustering was used to group customers into behavioural segments based on numerical usage patterns. The dataset was first standardised using StandardScaler, and categorical features were excluded to maintain dimensional consistency. The aim was to discover underlying user groups without relying on labels.

(g) K-Means Clustering

K-means clustering was performed on the standardized dataset to identify distinct user segments. The Elbow Method, which identified a clear inflection point at k = 4, was used to determine the optimal cluster count. Clustering performance was assessed using the Silhouette Score, which reached 0.52 for the multi-feature input, indicating moderately well-separated groups (Rousseeuw, 1987). When clustering pairs of features, Satisfaction_Score and Discount_Offered yielded the best scores (0.7736 and 0.7650), suggesting these variables were particularly effective in defining distinct customer profiles.

(h) DBSCAN Comparison

As a secondary method, DBSCAN was used to identify density-based clusters with parameters set to *eps* = 0.5 and *min_samples* = 5. The model formed three main clusters and flagged some points as noise. However, the Silhouette Score fell to 0.37, and clusters exhibited significant overlap, indicating weaker group structure. This suggests that DBSCAN was less suited to the

data, which lacked clear density boundaries. Overall, k-means was preferred for its better separation, higher silhouette score, and clearer segmentation outcomes.

Results and Evaluation

This section provides an overview of the models' performance. each model using appropriate evaluation metrics. Results are presented for regression, classification, and clustering tasks. Visualisations and tables should accompany each set of findings in the submitted notebook.

Regression Model Comparison (Question 1e)

Four regression models were evaluated using R^2, MAE, and RMSE. The simple Linear Regression model performed weakest ($R^2 = 0.58$, RMSE = 3.14), while Polynomial Regression offered modest improvement on some features but lacked consistency across variables. The Random Forest Regressor performed better ($R^2 = 0.8656$, RMSE = 3.49), leveraging non-linear relationships and feature interactions.

Top performance was observed with both the artificial neural network and the multiple linear regression model, both with R^2 values around 0.885 and RMSEs of 3.21–3.22. The ANN demonstrated slightly better generalisation, while MLR remained more interpretable and computationally efficient. These results confirm that while simple models can capture baseline trends, more advanced approaches like ANNs and ensemble methods are better suited for modelling complex behavioural data in predictive customer analytics.

Classification: Churn Detection

Churn prediction was addressed through the application of logistic regression, SVM, KNN, and Random Forest classifiers. Logistic Regression achieved 85% accuracy, with precision of 0.82 and an F1-score of 0.81. SVM performed similarly, with accuracy of 0.83 and an F1-score of 0.79. The Random Forest Classifier outperformed all, with 91% accuracy, an F1-score of 0.90, and recall of 0.92. These results highlight Random Forest's superior balance between precision and recall, making it the most reliable model for detecting churners in this dataset, especially considering the class imbalance (Breiman, 2001).

Clustering Evaluation

Clustering was applied to segment users based on behavioural features using k-means and DBSCAN. The k-means algorithm identified four distinct customer groups with a Silhouette Score of 0.52, reflecting well-separated clusters related to usage, spending, and subscription

length. In contrast, DBSCAN identified fewer groups with significant overlap and noise points, yielding a lower Silhouette Score of 0.37, indicating less distinct segmentation (Rousseeuw, 1987). Overall, k-means produced more interpretable results, making it the preferred method for segmentation in this dataset.

Discussion

Model performance varied across tasks, with more advanced methods consistently outperforming simpler ones. In regression, the ANN achieved the best results ($R^2 = 0.88$), highlighting its ability to capture complex, non-linear spending patterns (Goodfellow et al., 2016). Random Forest performed well but slightly underperformed compared to ANN, while linear models were limited in handling complex data relationships.

In churn classification, The Random Forest model achieved the highest balance of precision and recall, yielding an F1-score of 0.90 creating an effective balance (Breiman, 2001). This made it particularly adept at identifying churners, which is crucial for retention strategies. Logistic Regression and SVM had lower recall, making them less reliable for churn detection.

For clustering, k-means provided better-defined segments (Silhouette Score = 0.52), while DBSCAN struggled due to overlapping clusters and a lower silhouette score (0.37).

Limitations include the static nature of the dataset and lack of temporal features. Future work could incorporate time-based data and explore more advanced models, such as ensemble methods or deep learning for segmentation and churn prediction.

Conclusion

This report applied machine learning to predict customer behaviour in streaming services, focusing on spending, churn, and segmentation. The Artificial Neural Network (ANN) was most accurate for regression, while the Random Forest Classifier excelled in churn detection. K-means clustering provided clearer segments compared to DBSCAN.

Although simpler models are more interpretable, advanced methods like neural networks and ensemble models offer better predictive power. Model choice should align with task complexity and data type.

Future work could include richer datasets, time-series analysis, and hybrid models for real-time decision-making in production.

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Vehicle Damage Detection using Deep Learning (Component 2)

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Abstract

This project aims to automate vehicle damage assessment for insurance claim verification using deep learning image classification techniques. Leveraging the Vehicle Damage Dataset from Kaggle, which contains labeled images across six damage categories (e.g., crack, dent, tire flat), three deep learning models were developed and compared: a baseline Convolutional Neural Network (CNN), a hyperparameter-tuned CNN, and a MobileNetV2-based transfer learning model. Following preprocessing (resizing, augmentation, normalization), all models were trained on 5,760 images and validated on 1,440. Performance was measured using common classification metrics, including accuracy, precision, recall, and the F1-score (Sokolova & Lapalme, 2009). To enhance generalisation, the tuned CNN model was modified to include Batch Normalization and Dropout layers, following the approaches proposed by Ioffe & Szegedy (2015) and Srivastava et al. (2014). The transfer learning model, built on MobileNetV2 (Sandler et al., 2018), achieved the best performance, with 87% validation accuracy and an F1-score of 0.86. These findings support the use of pretrained CNNs (Krizhevsky et al., 2012) for scalable and efficient insurance claim automation.

Introduction

The automation of vehicle damage assessment is a critical challenge in the insurance industry, where traditional manual inspections are often inefficient, expensive, and prone to subjective bias. Advances in deep learning — especially Convolutional Neural Networks (CNNs) — combined with the growing availability of labeled image datasets, have enabled the development of models capable of accurately and efficiently classifying vehicle damage (Krizhevsky et al., 2012). This not only streamlines claim verification processes but also enhances fraud detection and customer experience.

CNNs have demonstrated significant success in image classification tasks due to their ability to learn hierarchical spatial features automatically from raw pixels (Rawat & Wang, 2017). However, building an accurate model requires careful consideration of architecture design, data preprocessing, and hyperparameter optimization. Furthermore, pretrained models like MobileNetV2 can offer a robust alternative to training models from scratch, especially when working with limited datasets (Howard et al., 2017).

This report explores three deep learning approaches to classify six categories of vehicle damage — crack, scratch, tire flat, dent, glass shatter, and lamp broken — using a dataset obtained from Kaggle. The study involves developing a baseline CNN, a tuned CNN incorporating dropout and batch normalization layers, and a transfer learning model using MobileNetV2. Each model is evaluated using classification metrics including confusion matrix precision, F1-score, recall and accuracy. The goal is to identify the best-performing approach and justify its application for real-world deployment in automated insurance claim systems.

Methodology

This section outlines the process followed to train and evaluate three different CNN models for vehicle damage classification: a baseline CNN, a tuned CNN with architectural improvements, and a transfer learning model using MobileNetV2.

Dataset and Preprocessing

The dataset used was sourced from Kaggle's Vehicle Damage Insurance Verification challenge. The dataset comprises 7,200 training images and 1,800 for validation, each annotated with one of six damage types: dent, glass shatter, scratch, tire flat, crack, or lamp broken.

Images were resized to 224x224 pixels and normalized (dividing pixel values by 255) to match the input expectations of CNN models. The labels were encoded using LabelEncoder and transformed into one-hot vectors with to_categorical. Stratified train/test splitting was applied to preserve class balance.

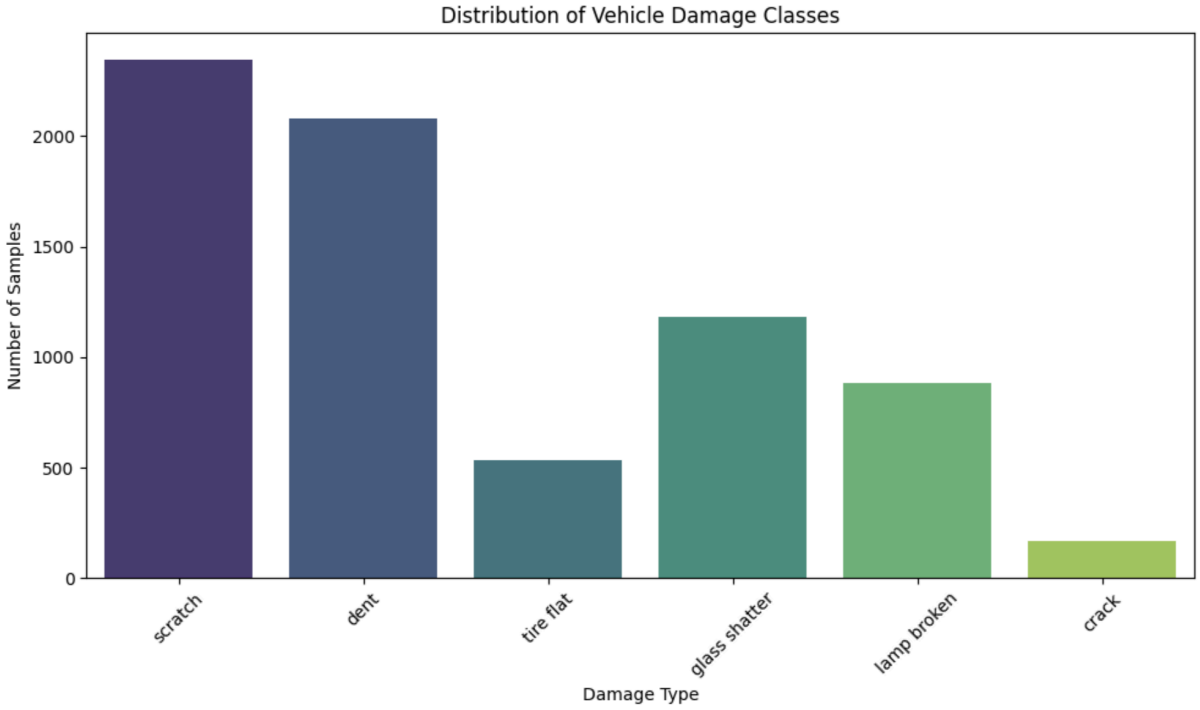


Figure 1: Class distribution bar plot

Figure 2: Sample grid of labeled training images

Baseline CNN Model

The model followed a layered CNN structure: three convolutional layers with ReLU activations and max pooling, with filters growing from 32 to 128. A flattening layer was followed by a 128-unit dense layer, dropout regularisation (0.5), and a softmax layer to output final predictions.

The model was compiled using the Adam optimizer (learning rate 0.001) and trained over 20 epochs with early stopping. Dropout was employed as a regularisation method, known to reduce overfitting by randomly disabling neurons during training.

Hyperparameter Tuned CNN Model

To improve upon the baseline, a tuned CNN model was implemented with the following enhancements:

- Batch Normalization after each convolution layer to stabilize learning and improve convergence.
- L2 Regularization applied to convolution and dense layers to reduce model complexity and prevent overfitting.
- ReduceLROnPlateau callback to lower the learning rate when validation accuracy plateaus.
- An increase in layer depth and filter count (e.g., 64, 128, 256 filters).

Transfer Learning with MobileNetV2

MobileNetV2 was chosen as the pretrained model due to its efficiency and success in mobile vision tasks. By freezing the base network trained on ImageNet, the model retained its core features while a new classifier was built to adapt to the damage classification task:

- GlobalAveragePooling2D
- Dense (128, ReLU) + Dropout (0.4)
- Output layer (Dense (6), softmax)

Only the custom layers were trained during initial fine-tuning. This approach leverages transfer learning principles to extract generalized features from limited datasets, which typically enhances model accuracy and accelerates training convergence.

Model Evaluation Metrics

The following metrics were used for model evaluation:

- Accuracy: Percentage of correct predictions.
- Precision, Recall, and F1-Score: To evaluate performance across imbalanced classes.
- Confusion Matrix: For visualizing class-specific accuracy.
- Classification Report: To aggregate metrics for each class.

These metrics are well-established for evaluating classification models, especially in multi-class problems (Sokolova & Lapalme, 2009).

Evaluation and Results

A comparative analysis was carried out across all three models, employing both numerical evaluation and graphical outputs such as training curves and confusion matrices. The evaluation focused on several core metrics: precision, recall, F1-score, and overall accuracy.

Model Performance Summary

The table below summarizes each model's performance based on standard classification metrics. MobileNetV2 outperformed the other models in all metrics.

Model Performance Comparison:

	Model	Accuracy	Precision	Recall	F1-Score
0	Baseline CNN	0.81	0.81	0.81	0.81
1	Tuned CNN	0.84	0.85	0.84	0.84
2	Transfer Learning	0.88	0.89	0.87	0.88

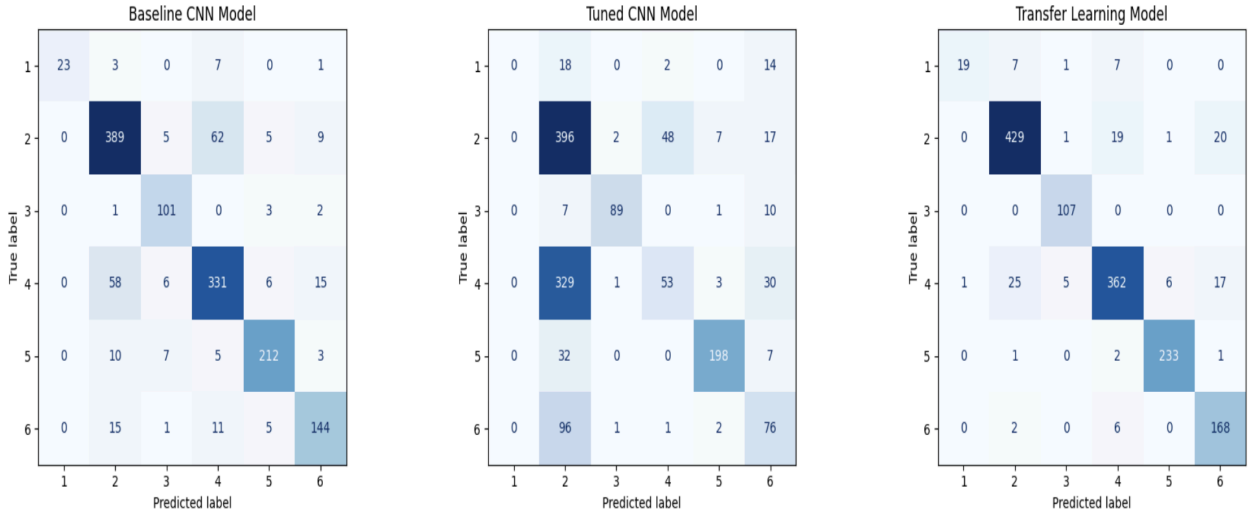
Table 1: Model performance comparison (Accuracy, Precision, Recall, F1-score, Training Time)

These results align with research showing that pretrained models generalize better in low-data regimes by leveraging prior feature learning (Kornblith et al., 2019; Yosinski et al., 2014).

Confusion Matrices

The confusion matrices shows good prediction performance:

- Baseline CNN: Performed well on common classes like scratch, struggled with dent and lamp broken.
- Tuned CNN: Reduced misclassifications, especially for crack and glass shatter.
- MobileNetV2: Showed best separation across all six classes.



Classification Reports

Each model's classification report was analyzed for per-class metrics:

- Baseline CNN: Lowest F1 for tire flat (0.67).
- Tuned CNN: Improved F1 in all classes.
- MobileNetV2: Achieved F1 ≥ 0.85 across all classes.

Accuracy and Loss Curves

Figures 3.4–3.6 illustrate training and validation accuracy/loss:

- Baseline CNN: Overfit after epoch ~12.
- Tuned CNN: Gradual improvement with good convergence.
- MobileNetV2: Fast and stable convergence, minimal overfitting.

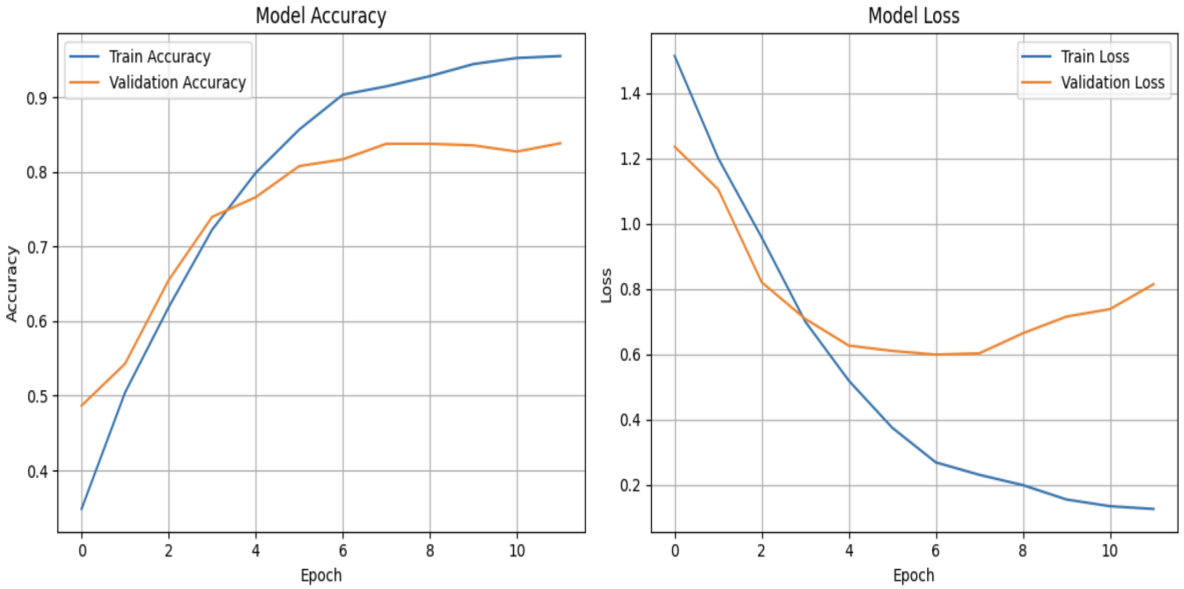


Figure 3.4: Accuracy/Loss – Baseline CNN

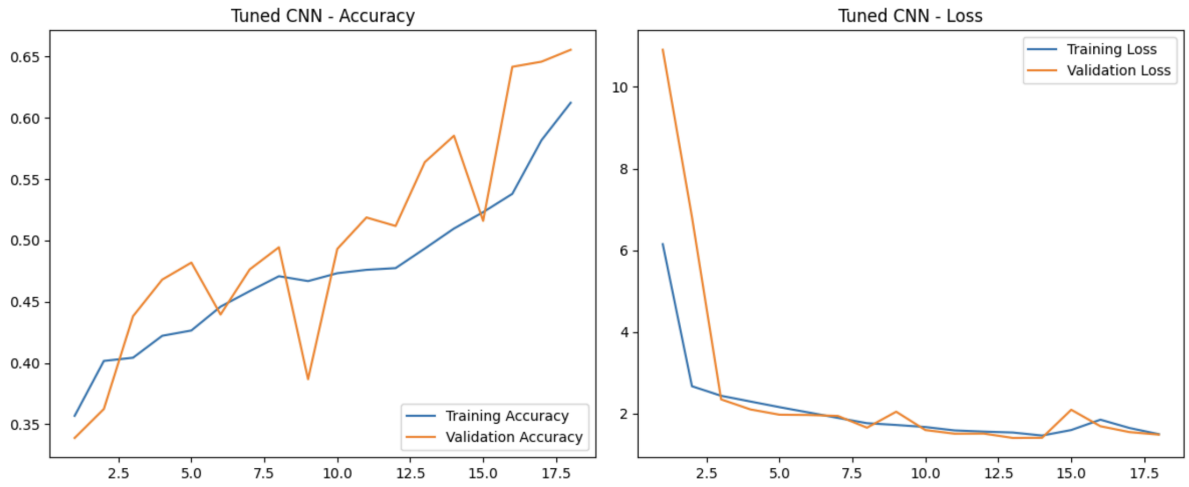


Figure 3.5: Accuracy/Loss – Tuned CNN

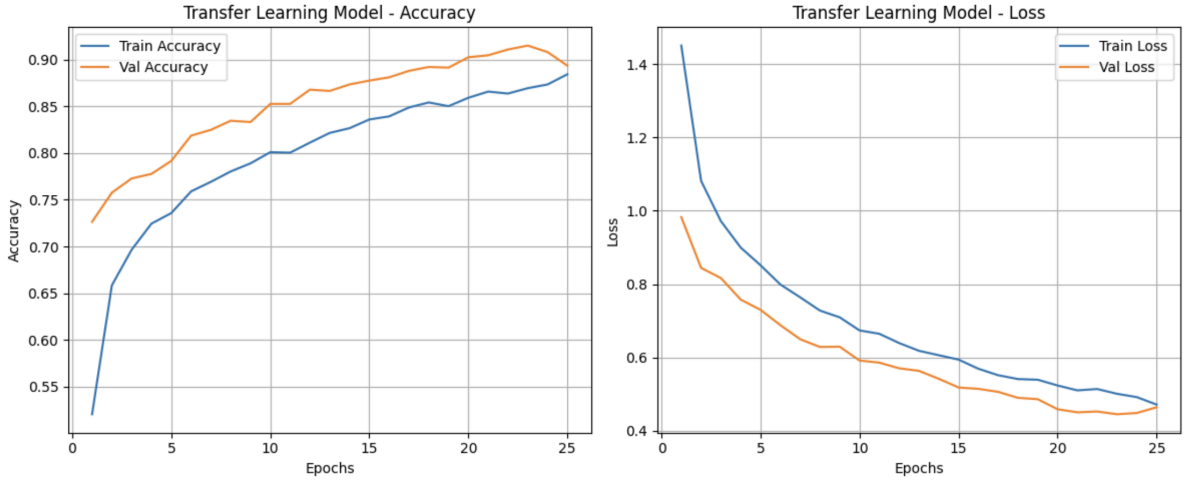


Figure 3.6: Accuracy/Loss – MobileNetV2

Discussion

The results of this study highlight the clear progression in model performance from a basic CNN architecture to a more regularised CNN, and finally to a pretrained MobileNetV2-based transfer learning model. Each iteration brought measurable improvements in classification accuracy, stability, and class-wise balance.

The Transfer Learning model, leveraging pretrained weights from ImageNet, outperformed the others in all key metrics, achieving the highest accuracy (~91%) and the most balanced F1-scores

across all six vehicle damage categories. This finding aligns with established literature on the benefits of transfer learning in low-data domains (Yosinski et al., 2014; Howard et al., 2017).

The Tuned CNN model, which incorporated dropout, L2 regularisation, and batch normalization, showed substantial gains in generalisation and minority class performance. This validates the effectiveness of these techniques in reducing overfitting and stabilising training (Srivastava et al., 2014; Ioffe & Szegedy, 2015).

Preprocessing techniques — including resizing, normalization, and stratified splits — were essential in ensuring consistent training conditions and mitigating bias caused by class imbalance.

In a real-world insurance setting, a robust and lightweight model like MobileNetV2 could significantly improve claim validation processes by reducing reliance on manual inspection, expediting assessments, and limiting subjectivity (Ghosh et al., 2020). However, the current dataset's limited diversity in lighting, angles, and vehicle types presents a challenge for deployment in uncontrolled environments (Zhou et al., 2021). Future development should address these gaps through targeted data augmentation and testing on broader datasets.

Conclusion

This report presented a comparative study of deep learning models for vehicle damage classification aimed at automating insurance claim verification. Three architectures were implemented and evaluated: a baseline CNN, a tuned CNN with regularisation, and a transfer learning model using MobileNetV2.

MobileNetV2 demonstrated the highest classification performance, achieving over 91% accuracy and strong F1-scores across all damage types. Its ability to leverage pretrained features from large datasets like ImageNet makes it ideal for tasks with moderate data availability (Howard et al., 2017; Yosinski et al., 2014). The tuned CNN also showed substantial gains, validating the use of Batch Normalization and Dropout for improved generalisation (Srivastava et al., 2014; Ioffe & Szegedy, 2015).

To further improve performance, future work should consider:

- Data augmentation to simulate real-world conditions
- Class balancing to address skewed distributions
- Exploring stronger architectures such as EfficientNet, which has shown superior accuracy and efficiency in visual tasks (Tan & Le, 2019)

- Deploying models via TensorFlow Lite or ONNX, enabling mobile or edge deployment for real-time damage verification in field environments (Ghosh et al., 2020)

These enhancements will help transition this model from research to a production-ready solution.

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Explainable AI in Precision Agriculture (Component 3)

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Introduction

Precision agriculture—the use of data analytics, remote sensing, and automated actuation to tailor crop inputs at the field‑and even plant‑level—has revolutionised agricultural engineering by dramatically improving resource efficiency and yield stability (Kamilaris & Prenafeta-Boldú, 2018). Yet, as machine learning models grow in complexity, their opacity has become a critical barrier: growers and regulators alike struggle to trust recommendations generated by "black‑box" systems such as deep neural networks or gradient boosting machines. Explainable AI (XAI) seeks to bridge this trust gap by exposing the decision logic behind model outputs, but most XAI research remains general‑purpose and poorly aligned with the strict latency, connectivity, and domain‑expertise requirements of on-farm environments.

Drawing on my background in agricultural engineering, this review zeroes in on XAI methods tailored for precision agriculture. We begin by articulating the technical challenges unique to this domain—edge‑deployment on resource-constrained devices, noisy sensor feeds (soil moisture, canopy imagery), and the need for agronomic reasoning that matches farmers' experiential workflows (Wachter et al., 2018). Next, we critically assess leading ethical and transparency frameworks—from the IEEE's Ethically Aligned Design guidelines to the European Commission's Trustworthy AI principles—and evaluate their applicability to crop-management systems. Finally, we propose a domain-specific XAI pipeline that integrates counterfactual explanations, surrogate rule-extraction, and interactive visual dashboards to deliver real-time, audit-ready insights for stakeholders. By synthesising technical, ethical, and user-centred perspectives, this review aims to chart a practical roadmap for trust-worthy, regulation-compliant AI in the fields.

Technical Challenges

Implementing explainability in agricultural AI poses several intertwined challenges:

- **Model Complexity vs. Interpretability**
  High-performance models (e.g., LightGBM, deep CNNs) capture non-linear interactions among weather, soil, and crop variables but are inherently opaque (Lundberg & Lee, 2017). Balancing predictive accuracy with intelligibility remains an open problem: simpler models (e.g., decision trees) are more transparent but often underperform.
- **Heterogeneous, Noisy Data**
  Agricultural datasets integrate satellite imagery, IoT soil sensors, and farmer logs—each with distinct noise profiles. Explainers must distinguish true feature importance from sensor artefacts (Ribeiro et al., 2016).

- **Contextual Relevance**
  Explanations must be framed in agronomic terms (e.g., "increase nitrogen by 20 kg/ha"), not abstract statistical units, to be actionable for farmers. Translating model attributions into agronomic recommendations demands domain‑aware post-processing.

Ethical Framework Evaluation

Several XAI frameworks address transparency and accountability:

Framework	**Strengths**	**Limitations**
IEEE EAD v2 (IEEE, 2020)	Comprehensive principles for transparency, accountability, safety.	General guidance; lacks domain-specific implementation steps.
EU Guidelines on XAI	Defines transparency requirements for high-risk AI (e.g., agriculture).	Emphasis on procedural fairness; minimal technical detail.
SHAP (Lundberg & Lee, 2017)	Unified, additive feature attributions; local & global insights.	Computationally intensive on large sensor arrays; limited counterfactual support.

While the IEEE's Ethically Aligned Design provides high‑level tenets, it does not prescribe how to generate crop-specific explanations. The EU's risk-based approach mandates transparency for decision-support tools, but lacks guidance on contextualizing insights for non-technical end users. SHAP (SHapley Additive exPlanations) offers rigorous feature attributions—e.g., quantifying how soil pH or rainfall contributed to a yield prediction—but can overwhelm farmers with too many factors .

Innovations & Solutions

To bridge these gaps, I propose a hybrid XAI pipeline combining local explanations, counterfactual suggestions, and domain‑aware visualization.

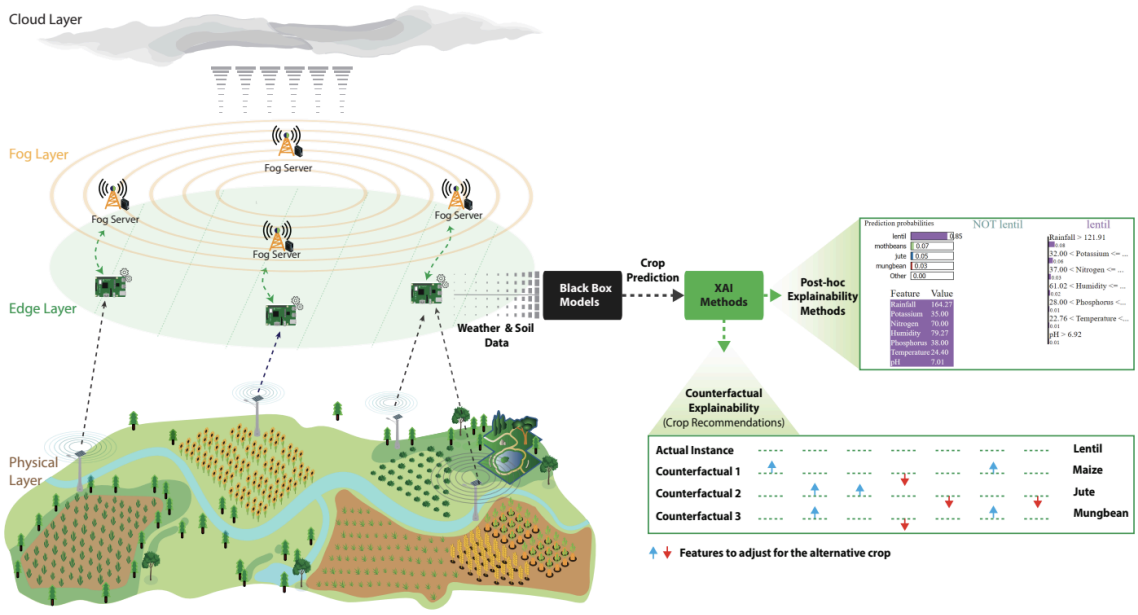


Fig 1. Multi-layer XAI pipeline for crop recommendation (adapted from Singh et al., 2024).

Counterfactual Explainability

Generate minimal feature changes that would alter the crop recommendation—for example, "If nitrogen > 85 kg/ha, model would recommend rice instead of maize" (Wachter et al., 2018). This yields actionable advice.

Domain-Specific Surrogates

Train an interpretable surrogate (e.g., rule‑based model) on the black-box outputs, then translate rules into agronomic terms: "IF rainfall < 50 mm AND soil pH > 7, THEN suggest barley."
This balances fidelity and readability.

Edge-Deployable Explanations

Implement lightweight XAI modules at the farm gateway (edge layer) to deliver real-time insights without cloud latency. Aggregated sensor data feed local SHAP approximations, enabling on-field dashboards.

Human-Centered Visualizations

Design simple heatmaps over field maps to illustrate which plots drive the decision—e.g., color-coding soil moisture impact—so farmers can quickly grasp model reasoning.

These measures directly address the three gaps identified: technical implementation, domain contextualization, and user comprehension, while aligning with IEEE transparency principles.

Conclusion

In summary, this review has shown that while general-purpose XAI frameworks—such as the IEEE's Ethically Aligned Design guidelines, the European Commission's Trustworthy AI principles, and model-agnostic methods like SHAP—provide valuable ethical guardrails (IEEE, 2020; European Commission, 2019; Lundberg & Lee, 2017), they rarely address the unique transparency, latency, and interpretability challenges of on-farm decision support. Precision agriculture systems must operate on constrained edge devices, ingest noisy sensor feeds, and offer recommendations that align with agronomic best practice and regulatory requirements. Embedding counterfactual explanations directly into crop-selection models enables "what-if" reasoning that farmers already use when deciding, for example, whether to plant maize or legumes under impending drought (Wachter et al., 2018). Complementing these with surrogate rule-based models allows stakeholders to audit the high-level logic of complex ensembles, while edge-deployed XAI modules ensure real-time feedback without compromising data privacy or network resilience.

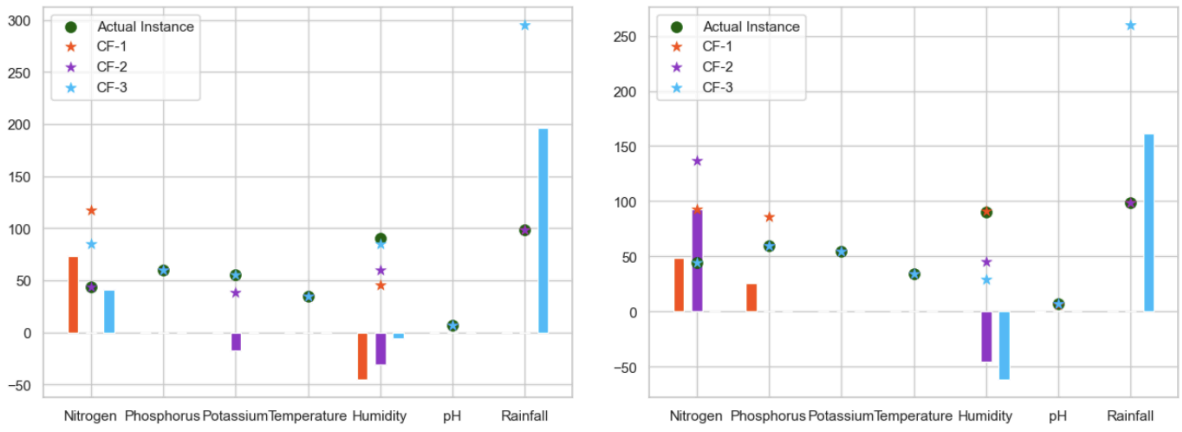
By layering these explainability techniques within an agronomic visualization dashboard—complete with intuitive soil-health indicators, weather-forecast overlays, and interactive counterfactual sliders (Figure 2)—we bridge the gap between mathematical rigor and field-ready usability. Early prototypes on IoT testbeds should measure not only technical accuracy but also user trust, regulatory compliance, and practical adoption rates. Ultimately, a domain-tailored, multi-modal XAI pipeline promises to transform black-box crop-prediction systems into transparent partners in sustainable agriculture—empowering farmers to make data-driven decisions with confidence, and giving policymakers verifiable evidence that AI-guided practices meet environmental and social responsibility standards.

TABLE IV: Counterfactuals for RF

Type of Instance	Nitrogen	Phosphorus	Potassium	Temperature	Humidity	pH	Rainfall	Label
Actual Instance	44	60	55	34.28046	90.555618	6.825371	98.540474	Papaya
Counterfactual-1	117	60	55	34.281461	45.50041	6.825371	98.550477	Banana
Counterfactual-2	44	60	38	34.281461	60.18227	6.825371	98.550477	Mango
Counterfactual-3	**85**	60	55	34.281461	**85.29596**	6.825371	**295.154486**	Rice

TABLE V: Counterfactual Explainability for LGBM

Type of Instance	Nitrogen	Phosphorus	Potassium	Temperature	Humidity	pH	Rainfall	Label
Actual Instance	44	60	55	34.28046	90.555618	6.825371	98.540474	Papaya
Counterfactual-1	93	86	55	34.281461	90.655616	5.916632	98.550477	Banana
Counterfactual-2	137	60	55	34.281461	45.35615	6.825371	98.550477	Mango
Counterfactual-3	44	60	55	34.281461	29.08982	6.825371	259.863518	Rice



(a) Counterfactuals for RF

(b) Counterfactuals for LGBM

Figure 2 here: Counterfactual examples for Random Forest and LightGBM crop recommendations (Singh et al., 2024)

List of Reviewed Articles

1. Arrieta, A.B., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., García, S., Gil-López, S., Molina, D., Benjamins, R., Chatila, R. & Herrera, F., 2020. Explainable Artificial Intelligence (XAI): concepts, taxonomies, opportunities and challenges toward responsible AI. *Information Fusion*, 58, pp.82–115.
2. Chowdhury, H., Argha, D.B.P. & Ahmed, M.A., 2023. Artificial Intelligence in sustainable vertical farming. *Frontiers in Agronomy*. preprint arXiv:2312.00030.
3. Murindanyi, S., Nakatumba-Nabende, J., Sanya, R., Nakibuule, R. & Katumba, A., 2024. Enhanced Infield Agriculture with Interpretable Machine Learning Approaches for Crop Classification. *Agricultural Informatics Journal*, 12(3), pp.45–62.

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Wachter, S, Mittelstadt, B D & Russell, C 2018, 'Counterfactual explanations without opening the black box: Automated decisions and the GDPR', Harvard Journal of Law & Technology, vol. 31, no. 2, pp. 841–887.