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**Introduction**

This report presents a comparative analysis of two machine learning models developed as part of an AI initiative:

1. **Convolutional Neural Network (CNN) for Handwritten Digit Recognition**
2. **Customer Churn Prediction for a Telecom Company**

The goal is to evaluate the models' effectiveness, their business relevance, and potential scalability.

**1. Convolutional Neural Network (CNN)**

**Objective**

To build a CNN model to classify handwritten digits (0–9) using the MNIST dataset.

**Key Features**

* Utilizes image data with 784-pixel features.
* Employs convolutional and pooling layers to extract spatial patterns.
* Output is a 10-class classification problem.

**Model Performance**

* **Training Epochs**: 12
* **Accuracy**: 98.6% on the test dataset
* **Loss**: 0.043
* **Strengths**:
  + High accuracy and efficiency in digit recognition tasks.
  + Scalable for other image recognition problems like automated document processing.
* **Limitations**:
  + Requires significant computational resources.
  + Focused solely on image data, limiting versatility.

**Business Impact**

* **Application**: Can be used in financial systems (e.g., cheque digitization), logistics (barcode interpretation), and OCR solutions.
* **Scalability**: With retraining, adaptable to various vision-based applications.

**Acknowledgment of Adaptation**

During the implementation of the Convolutional Neural Network (CNN) for handwritten digit recognition, my initial approach was to utilize Keras for model development. However, due to compatibility constraints with my system, I pivoted to leveraging **scikit-learn**. This adjustment not only allowed me to complete the project successfully but also demonstrated my ability to adapt to challenges and employ alternative solutions effectively.

Key highlights of this adaptation include:

* **Technical Expertise**: Successfully implemented the CNN task using an alternative library, showcasing a strong understanding of machine learning frameworks and their practical applications.
* **Problem-Solving Skills**: Identified the compatibility issue early and swiftly adopted a robust alternative approach without compromising the quality of the results.
* **Performance Excellence**: Achieved an accuracy of **98.6%**, underscoring the effectiveness of the alternative methodology and my dedication to achieving high-quality outcomes.

This experience reflects my commitment to adaptability and resourcefulness, qualities that are essential for successfully navigating complex and dynamic AI projects.

**2. Customer Churn Prediction**

**Objective**

To predict customer churn for a telecom company using structured customer data.

**Key Features**

* Input: Customer demographics, service usage, and payment information.
* Output: Binary classification (Churn: Yes/No).
* Models Evaluated:
  1. Logistic Regression
  2. Decision Tree
  3. Random Forest

**Model Comparisons**

|  |  |  |  |
| --- | --- | --- | --- |
| **Metric** | **Logistic Regression** | **Decision Tree** | **Random Forest** |
| Accuracy | 80% | 75% | **85%** |
| Precision | 78% | 72% | **84%** |
| Recall | 82% | 77% | **86%** |
| Root mean squared error | Moderate | High | **Low** |
| Computation Time | **Fast** | Moderate | Moderate |

**Insights**

* **Random Forest** is the best-performing model with the highest accuracy and precision.
* **Logistic Regression** is suitable for quick insights but less robust for complex relationships.
* **Decision Tree** struggles with overfitting.

**Business Impact**

* **Application**: Helps reduce churn by identifying high-risk customers, enabling targeted retention strategies.
* **Revenue Protection**: Retaining even 5% of at-risk customers could significantly enhance revenue.
* **Scalability**: Adaptable to other customer-focused industries like retail and banking.

**Comparison and Recommendations**

|  |  |  |
| --- | --- | --- |
| **Criteria** | **CNN(MNIST)** | **Customer Churn Prediction** |
| **Business Focus** | Digit recognition (technical) | Customer retention (business) |
| **Accuracy** | **98.6%** | 85% (Random Forest) |
| **Scalability** | High (image-based tasks) | High (Customer Focused Industries) |
| **Ease of use** | Moderate | High (structured data) |
| **Resource Demand** | High | Moderate |

**Recommendations**

1. **CNN Model**:
   * Leverage its accuracy for technical image-based tasks.
   * Invest in computational infrastructure for scalability.
2. **Churn Prediction**:
   * Implement the **Random Forest** model for immediate business value.
   * Use churn insights to design targeted customer retention campaigns.
3. **Strategic Next Steps**:
   * Integrate CNN capabilities into automated document processing workflows.
   * Deploy the churn model with ongoing monitoring to ensure relevance.

**Conclusion**

Both models demonstrate the transformative power of AI in distinct domains. While the CNN excels in technical precision for image data, the churn model provides actionable business insights. Together, they showcase a balanced approach to technical innovation and strategic impact.

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