Report 3: AI Risk Prediction Tool – Final Report

1. Final Project Objectives

This study's main goal was to investigate the potential effects of artificial intelligence (AI) on employment in a range of industries. The objective was to forecast the vulnerability of certain jobs to AI-driven automation by examining real-world employment and AI adoption metrics. my goal was to develop models that could visualize patterns at the industry level and categorize employment into three AI risk levels: low, medium, and high. My final goal was to transform this study into a practical prototype Tool that would assist individuals in comprehending how AI disruption would affect their line of work.

2. Overview of the Dataset and Models

I used three main datasets:
- Ai_risk.csv: contained job titles, task volumes, and AI workload estimations.
- Cleaned_ai_job_market_insights.csv: included AI adoption data across industries.
- Cleaned_Analysis_AIAdoption_AutomationRisk.csv: provided job growth scores and automation potential.

These datasets were merged to create a comprehensive feature set: Tasks, AI models, AI Workload Ratio, and AI Impact Percentages.
The AI Impact column was label encoded into classes (0–n), and rare labels with less than 5 instances were filtered to improve model reliability.

A number of machine learning models were evaluated, such as K-Nearest Neighbors (KNN), Random Forest, Decision Tree, and Naive Bayes. However, Random Forest and XGBoost (Extreme Gradient Boosting) were the two models that performed the best. To address class imbalance, we created synthetic samples in underrepresented classes using the Synthetic Minority Oversampling Technique (SMOTE). In order to normalize input data for model performance, feature scaling was implemented using StandardScaler

3. Results and Interpretation

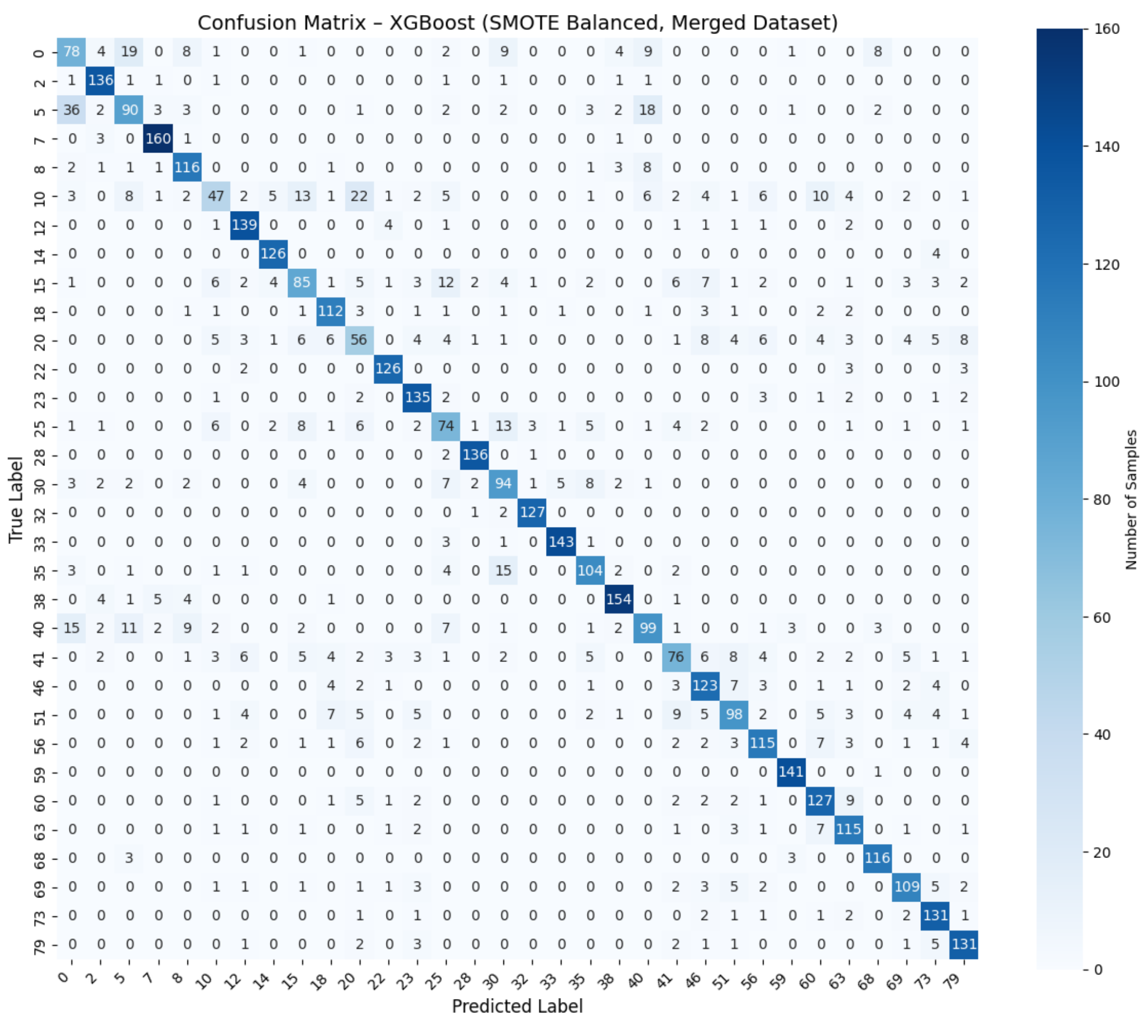
After data balancing and model optimization, the XGBoost model achieved an accuracy of 78.54% on the test set. Precision and recall scores were above 0.85 for many of the major classes, demonstrating good performance in predicting the AI risk level.

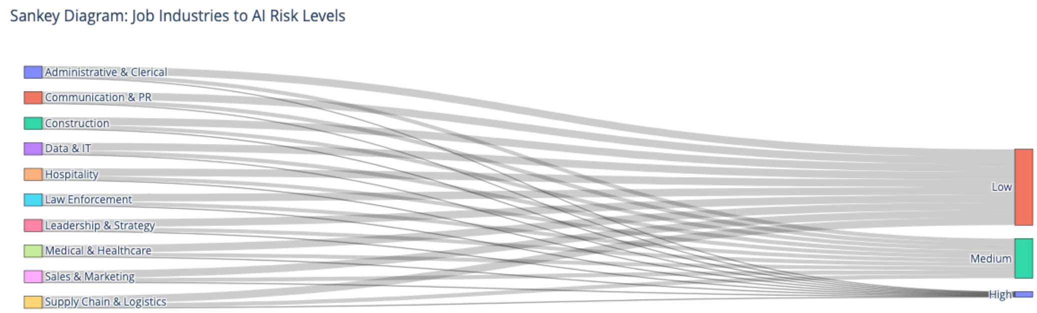
The confusion matrix (shown in Section 4) confirms that the model correctly classifies most jobs by their predicted AI impact. This result provides confidence in using this model as the core of an interactive tool.

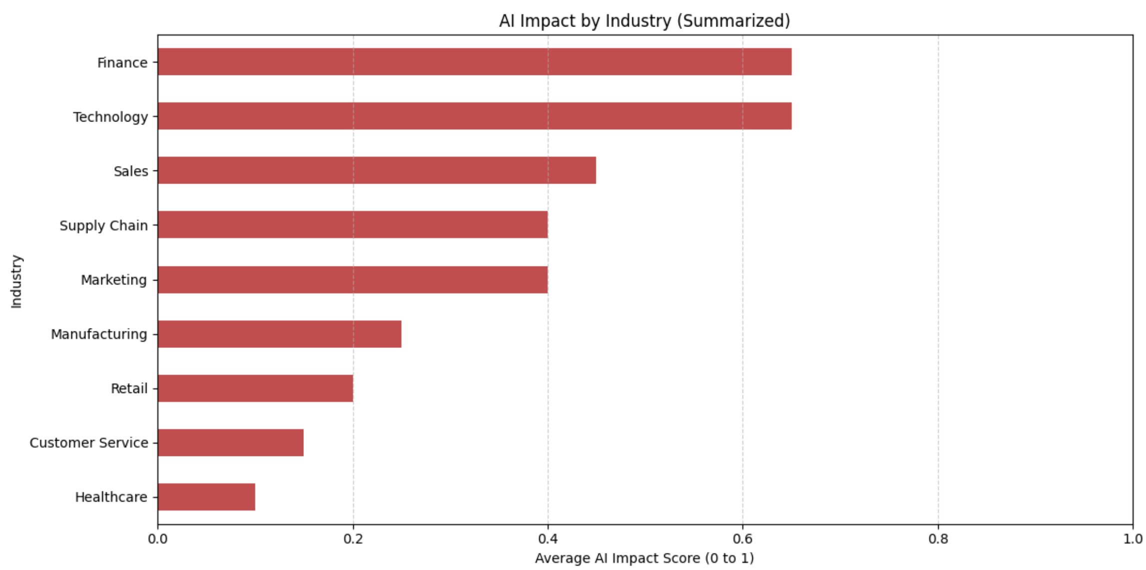
4. Visualizations and Analysis

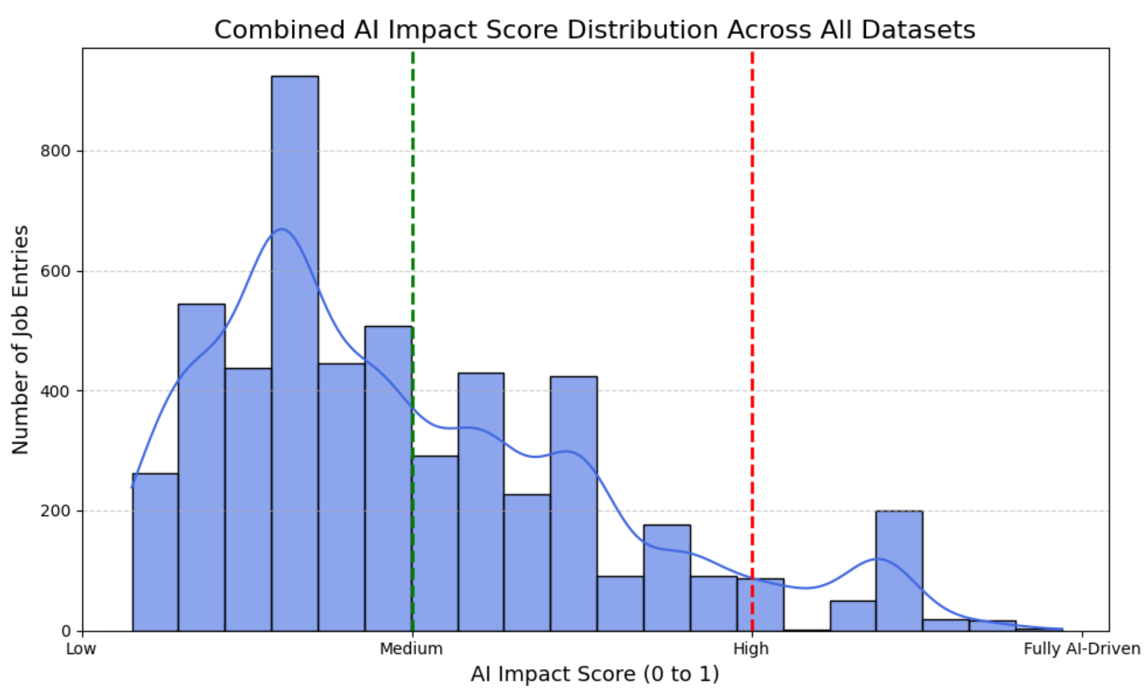
Several key visualizations were used to interpret the data:
- A confusion matrix to evaluate XGBoost performance across classes.
- A Sankey diagram showing job domains flowing into AI risk levels.
- A bar chart showing the average job growth score by industry.
- A histogram displaying the distribution of AI impact scores.

These visualizations provide both quantitative and qualitative insights into AI-driven disruption across sectors. For example, industries such as Marketing and IT tend to have higher AI workload ratios and thus face greater automation risk, while industries like Healthcare show resilience.




Sankey Diagram: Job Industries to AI Risk Levels
Administrative & Clerical
Communication & PR
Construction
Data & IT
Hospitality
Law Enforcement
Leadership & Strategy
Medical & Healthcare
Sales & Marketing
Supply Chain & Logistics
Low
Medium
High


AI Impact by Industry (Summarized)
Finance
Technology
Sales
Supply Chain
Marketing
Manufacturing
Retail
Customer Service
Healthcare
Industry
0.0
0.2
0.4
0.6
0.8
1.0
Average AI Impact Score (0 to 1)


Combined AI Impact Score Distribution Across All Datasets
Number of Job Entries
0
200
400
600
800
Low
Medium
High
Fully AI-Driven
AI Impact Score (0 to 1)

5. Challenges and Solutions

One of the major challenges was class imbalance many AI risk labels had very few examples. This was addressed using SMOTE, which allowed my models to generalize better. Another challenge was integrating multiple datasets with inconsistent formatting. We resolved this by renaming and aligning shared columns and handling missing values with median imputation. Memory limitations during training were solved by filtering rare labels and optimizing model parameters.

6. Final Deliverables

This final report includes:
- Cleaned and merged dataset used for modeling.
- A trained XGBoost model capable of predicting AI risk levels.
- A set of visualizations to communicate findings.
- Plans for an interactive tool to evaluate job risk using the trained model.

7. Evaluation and Reflection

I was able to meet the original project goals and extend them. The accuracy of the final model was significantly improved after applying data balancing and feature tuning. I also created informative visualizations that made the analysis more accessible. This project deepened my understanding of real-world machine learning, data integration, and the social impact of AI.

8. Recommendations for Future Work

1. Convert the current model into an interactive Streamlit Website to allow users to input their job titles and get risk predictions.
2. Improve job-title-to-feature mapping using NLP or external job classifications.
3. Incorporate more diverse and global datasets to improve model generalizability.
4. Add economic, educational, or geographic data to create more personalized recommendations.
5. Use explainable AI (e.g., SHAP) to help users understand why their job is at risk.

9. References

Kaggle Datasets:

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