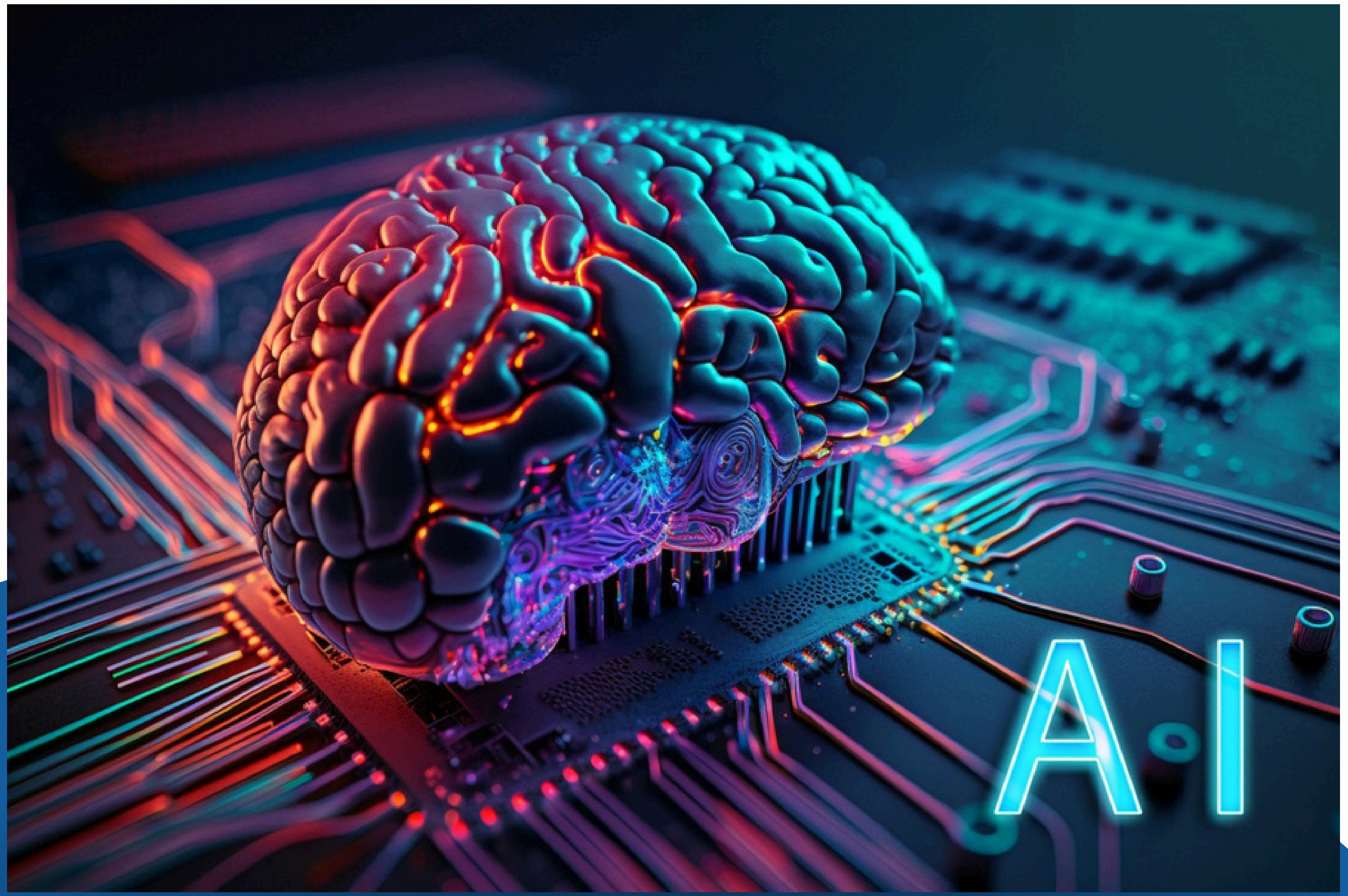
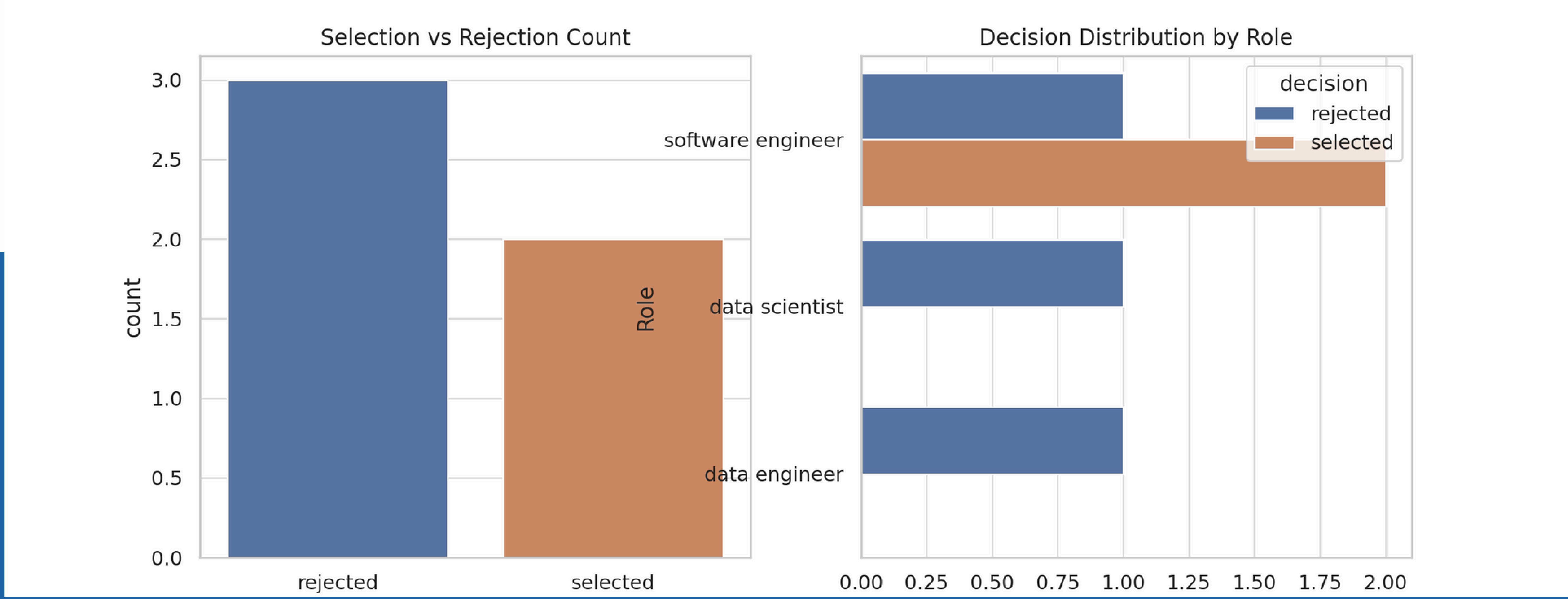
AI-Powered Automated Recruitment Pipeline

An AI-powered automated recruitment pipeline that screens resumes, selects candidates for interviews, generates AI-driven interview questions, enables AI-assisted interviews, evaluates candidates based on multiple factors, and automates result notifications to HR or managers.

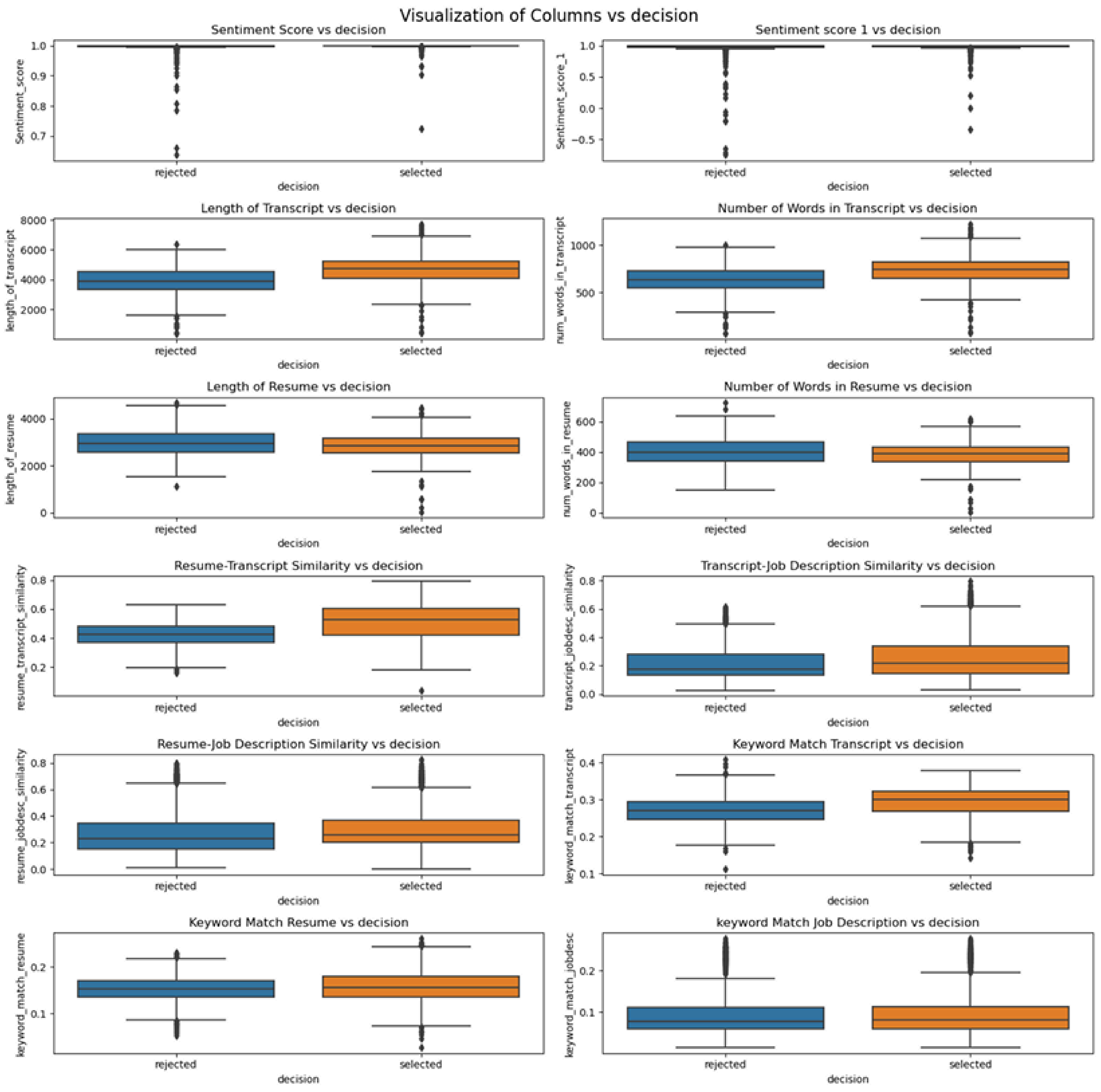


EXPLORATORY DATA ANALYSIS



- **Selection vs. Rejection Count:** This bar chart illustrates the overall number of selected and rejected candidates, providing a quick view of hiring trends.
- **Decision Distribution by Role:** This grouped bar chart shows how hiring decisions vary across different job roles, offering insights into selection rates for specific positions.

- **Sentiment Score:** Higher sentiment scores are linked to selection, but other factors are also important.
- **Transcript Length & Word Count:** Selected candidates often have longer transcripts and more words.
- **Resume Length & Word Count:** Candidates with more detailed resumes tend to be selected.
- **Similarity**: Higher similarity between resumes, transcripts, and job descriptions improves selection chances.
- **Keyword Match:** More relevant keywords in resumes and transcripts increase selection probability



Model Overview & Feature Engineering

Input Variables

- **ID**: Unique identifier for each candidate.
- **Name**: Candidate's name (could be used for identification but not for modeling).
- **Role**: The role the candidate applied for (categorical feature).
- **Transcript**: Candidate's interview responses (text feature).
- **Reason for Decision**: Reason behind the hiring decision (text feature).
- **Resume**: Candidate's resume (text feature).
- **Job Description**: The job description for the role (text feature).

Output Variable

- **Decision**: Target variable indicating whether the candidate was 'Selected' or 'Rejected'

Features Extracted

- **Text-based Features:** TF-IDF features for Transcript and Job Description.
- **Text Length & Word Counts**: Length and word count of Transcript and Resume.
- **Similarity Features:** Cosine similarity between Resume & Transcript, Transcript & Job Description, and Resume & Job Description.
- **Sentiment Features**: Sentiment Score for Transcript

Classical Machine Learning Models

Models :

- **Logistic Regression**: A linear model for binary classification.
- **Decision Tree:** A tree-based model for making decisions by splitting data.
- **Random Forest**: An ensemble model combining multiple decision trees.
- **XGBoost**: A gradient boosting model that improves predictions iteratively.

Best Model:

- **XGBoost**: Outperformed all other models with the highest accuracy (87.87%) and ROC AUC (0.970), making it the most effective for this classification task.

01

Logistic Regression:

- Accuracy: 77.01%
- ROC AUC: 0.848
- Strength: Effective for linear relationships, but limited with complex data.

02

Decision Tree:

- Accuracy: 80.16%
- ROC AUC: 0.906
- Strength: Good for capturing simple decision boundaries, though prone to overfitting.

03

Random Forest:

- Accuracy: 85.98%
- ROC AUC: 0.955
- Strength: Handles complex patterns and interactions, less prone to overfitting.

04

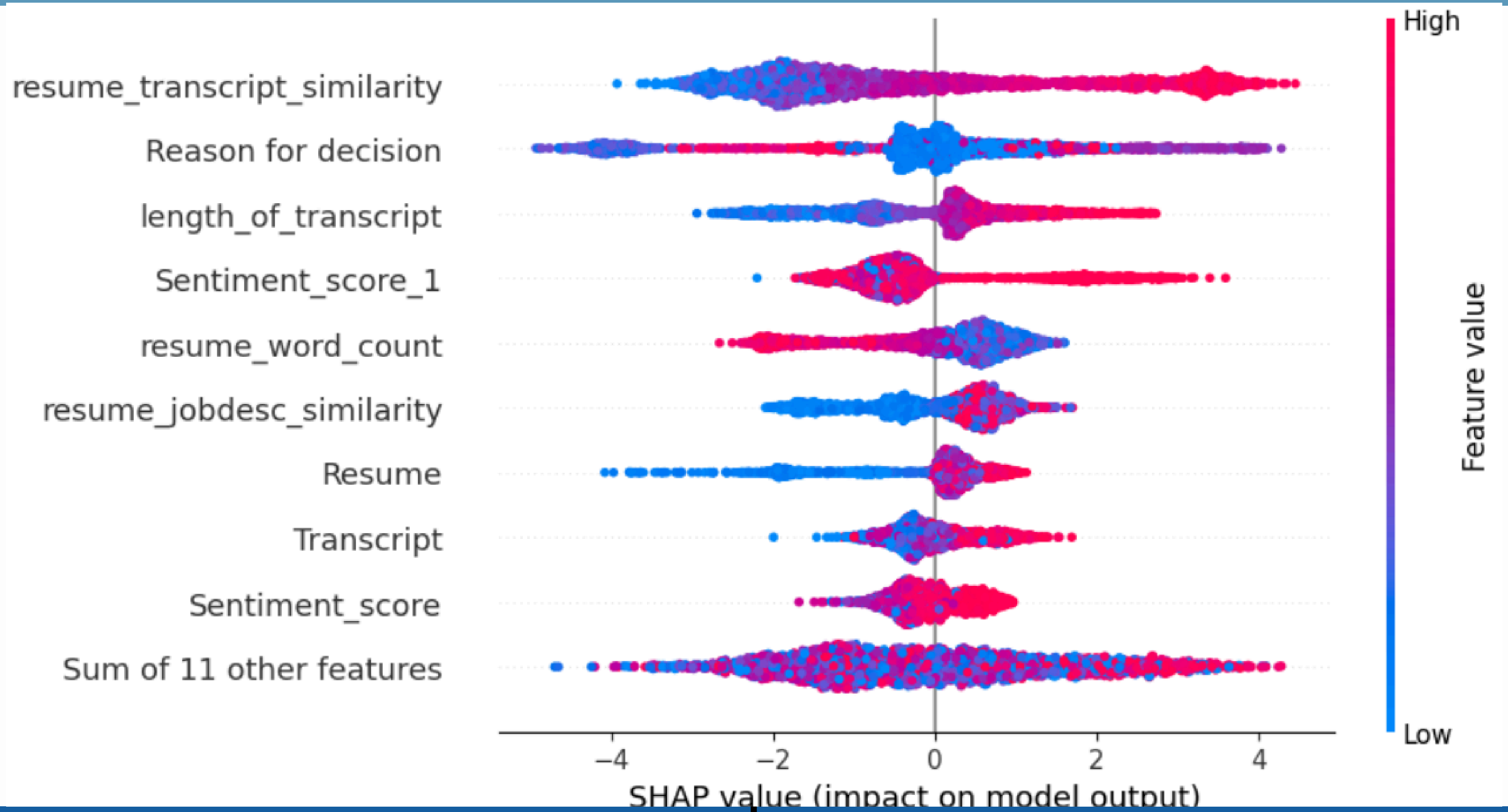
XGBoost:

- Accuracy: 87.87%
- ROC AUC: 0.970
- Strength: Excellent performance, especially with non-linear data.

DEEP LEARNING MODEL (BERT EMBEDDINGS)

1. **Model Overview:**
    - **BERT Embeddings**: Leveraged pretrained BERT (Bidirectional Encoder Representations from Transformers) to extract contextual embeddings from the Transcript and Job Description.
    - **Neural Network Architecture**: Built a Neural Network on top of the BERT embeddings for binary classification (Selected/Rejected).
2. **Approach:**
    - **Text Input:** Transcript and Job Description were tokenized and passed through BERT to capture semantic and contextual relationships.
    - **Additional Features:** Combined sentiment scores, similarity metrics, and word counts with the BERT embeddings.
    - **Output:** A neural network produced the probability of selection or rejection.
3. **Results:**
    - **Accuracy:** 82.36%
    - **ROC AUC:** 0.936
    - **Strengths:**
        - BERT's ability to understand contextual meaning from the text greatly enhanced performance.
        - The deep learning model performed better than traditional ML models, capturing more complex relationships in the data.
4. **Conclusion:**
    - The BERT-based Neural Network achieved solid results with an accuracy of 82.36% and ROC AUC of 0.936, demonstrating that leveraging BERT embeddings for text data classification is highly effective.

SHAP Analysis - Feature Impact



- **Top Influencing Feature**: resume_transcript_similarity has the highest impact on model predictions.
- **Other Key Features**: Reason for decision, length_of_transcript, and Sentiment_score_1 significantly affect outcomes.
- **SHAP Value Interpretation:**
- Positive SHAP values push predictions higher, while negative values lower them.
- Red (High Feature Value): Tends to increase the model's prediction.
- Blue (Low Feature Value): Tends to decrease the model's prediction.
- **Model Behavior:**
- Higher similarity between resume and transcript positively influences decisions.
- Sentiment scores and transcript length also play a role in shaping predictions.

SHAP Analysis: Key Insights

Waterfall Plot Interpretation

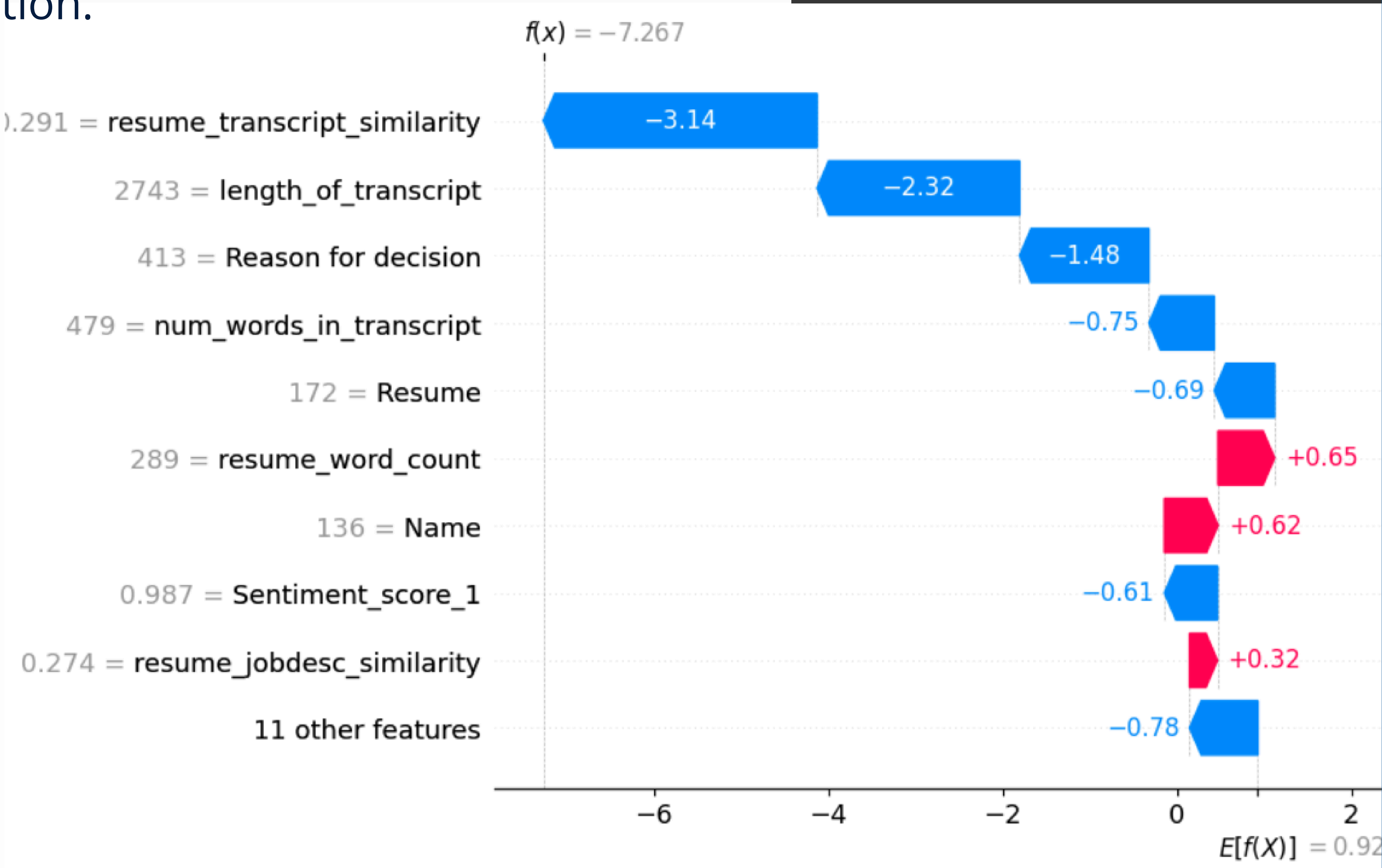
- **Base Value (E[f(X)]):** Average model prediction.
- **Final Prediction (f(x))**: Log-odds score for this instance.
- **Feature Contributions**:
    - **Negative (blue):** Reduced prediction.
    - **Positive (red):** Increased prediction.

Key Findings

- **Top Negative Features:**
    - resume_transcript_similarity (-3.14), length_of_transcript (-2.32) lowered the score.
- **Top Positive Features:**
    - Name (+0.65), resume_word_count (+0.62) had minor positive effects.

Business Takeaways

- Resume similarity strongly influences decisions.
- Long transcripts may negatively impact outcomes.



Power of Resume Screening AI

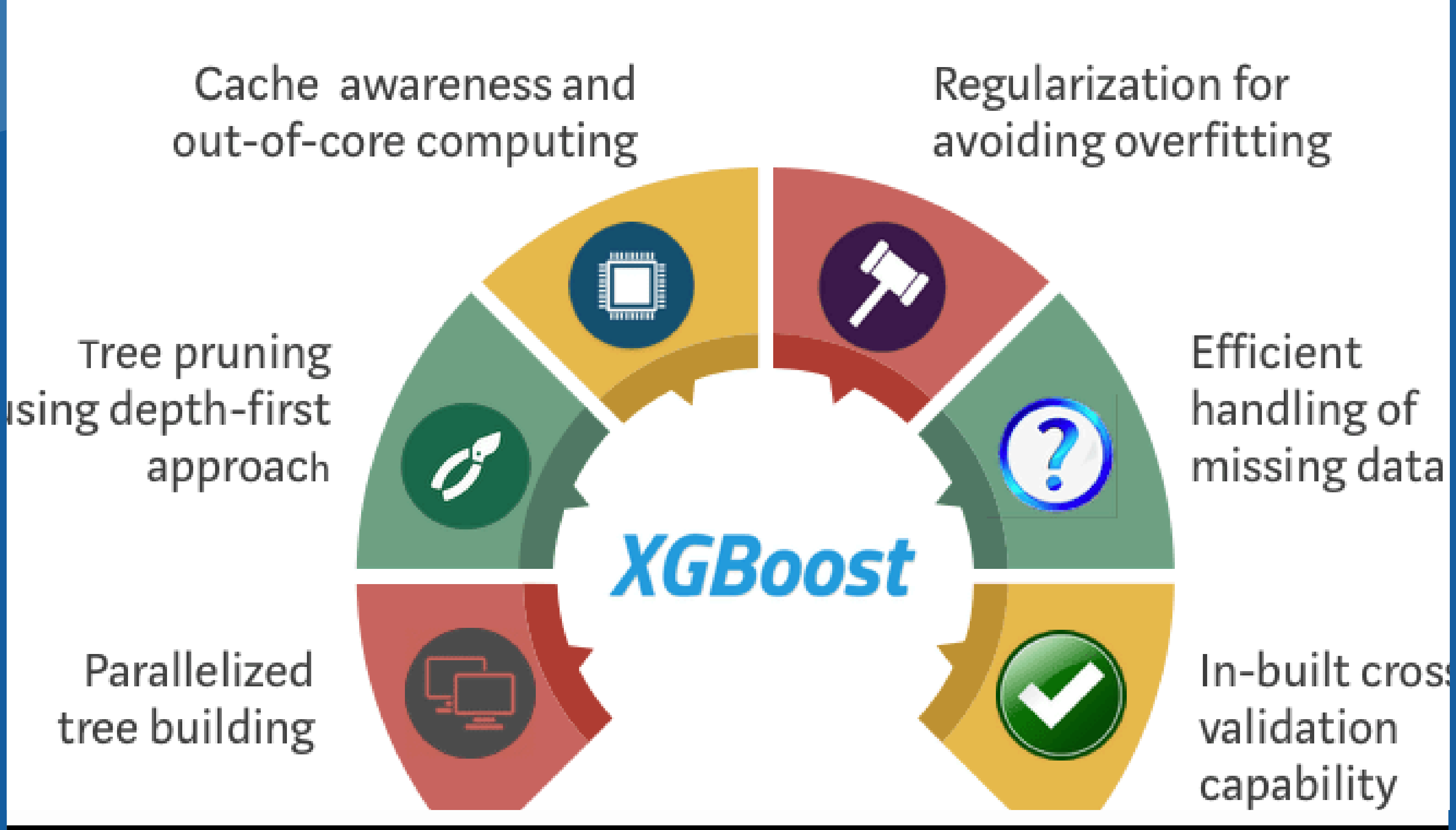
📌 How It Works?

1️⃣ **Resume Parsing** → Extracts text from resumes.
2️⃣ **Keyword Matching** → Identifies relevant job-specific keywords.
3️⃣ **Similarity Calculation** → Measures alignment between resume & job description (TF-IDF).
4️⃣ **Feature Engineering** → Adds attributes like sentiment score, length, and keyword count.
5️⃣ **Machine Learning Model** → Trained using Random Forest with hyperparameter tuning.
6️⃣ **Decision Output** → Classifies candidates as Selected or Rejected based on model predictions.

📊 Insights & Visualizations

✅ **Confusion Matrix** – Model performance evaluation.
✅ **Selection Rate by Job Role** – Understanding hiring trends.
✅ **Resume-Job Similarity Impact** – How alignment affects decisions.

Prediction & Automated E-mail



📌 AI-Powered Prediction

✅ Resume and job description processed using TF-IDF & Cosine Similarity.
✅ XGBoost Classifier predicts selection outcome with high accuracy.
✅ Advanced feature engineering (resume length, word count, similarity scores) enhances performance.

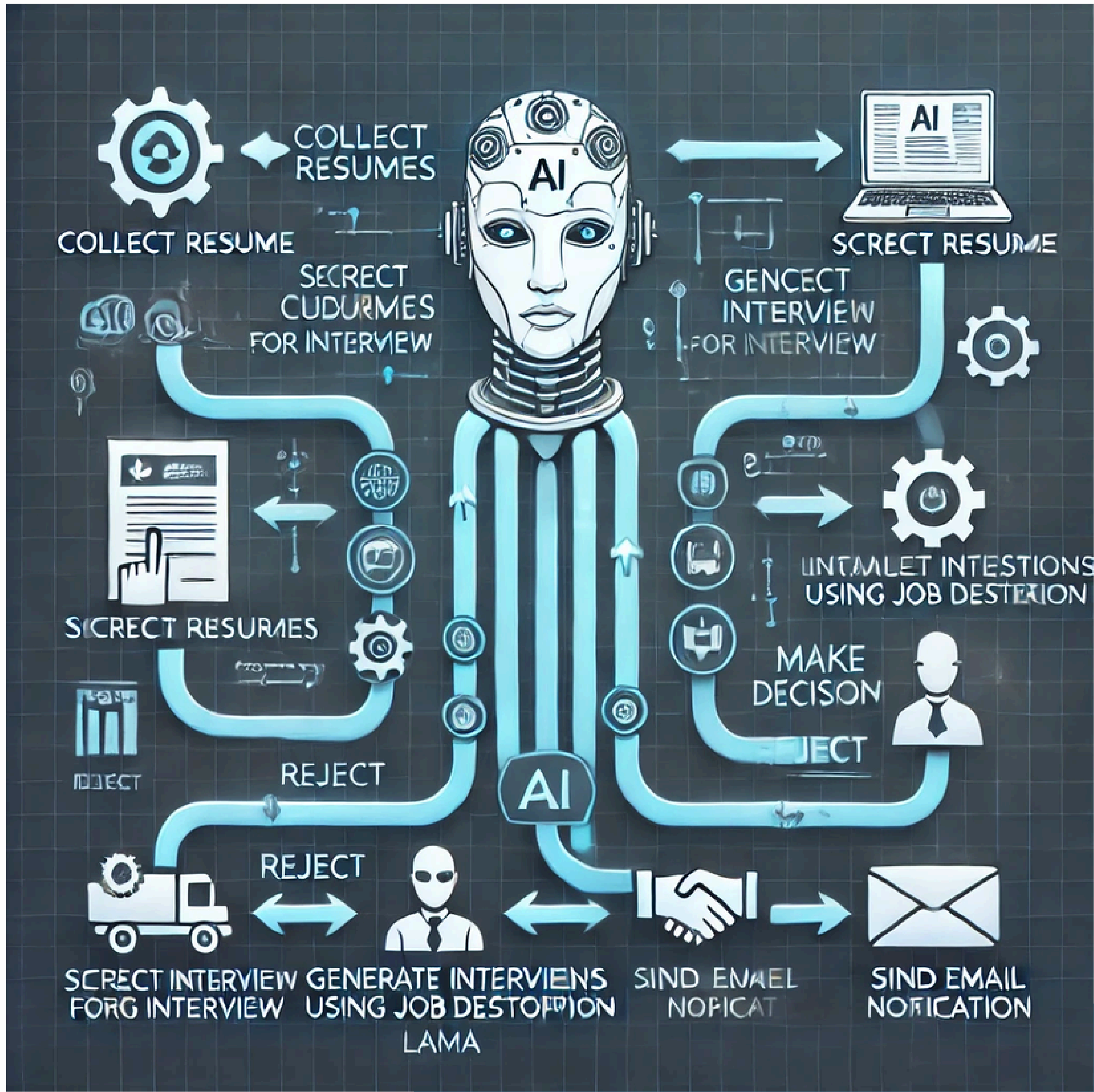
📌 Automated Email System

✅ Selected Candidates receive interview details.
✅ Rejected Candidates get a polite rejection email with feedback.
✅ Emails sent using SMTP/Gmail API/AWS SES for seamless communication

CONCLUSION

📂 **Collect Resume → 🤖 Screen Resumes (AI) → ✅ Select Candidates for Interview (AI) → 📝 Generate Interview Questions using JD (AI - Llama) → 🎤 Conduct Interview (AI or Human)→ 🏆 Make Decision (AI: Reject/Select) → 📧 Send Email Notification (AI)**

- **The AI-powered automated recruitment pipeline revolutionizes the hiring process by leveraging advanced machine learning and NLP techniques. From resume screening to interview conduction and final decision-making, AI enhances efficiency, reduces human bias, and accelerates candidate selection.**
- **By integrating AI-driven resume screening, Llama-powered question generation, and automated decision-making, organizations can streamline their hiring workflow, ensuring a data-driven, fair, and scalable recruitment process.**
- **This approach saves time, optimizes resources, and enhances hiring accuracy while improving candidate experience. Future advancements could include AI-driven talent search, multi-modal assessments (text, voice, and video analysis), deeper explainability in AI decisions, and continuous learning models—further refining recruitment strategies for greater efficiency, fairness, and precision.**



THANK YOU!