

Diabetic Readmission Risk Prediction

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Introduction

Healthcare Challenge: High Readmission Rates in Diabetic Patients

Objective: Predict 30-day readmission risk to enable proactive interventions

Goal: Reduce readmission rates and improve patient outcomes

Business Use Case

Financial Impact: High costs associated with readmissions

Patient Impact: Negative effects on health and quality of life

Solution: Machine learning system to identify high-risk patients

System Architecture

Components

Data Ingestion
Data Engineering
Feature Engineering
Model Training
Deployment

Technologies

DVC (Data Version Control)
Feast (Feature Store)
AutoGluon (Automated ML)

Data Sources

Dataset: Diabetes 130-US hospitals for years 1999-2008

Size: Over 100,000 patient records

Features: Demographics, medical history, lab results, medications, hospitalization details

Data Engineering

Data Ingestion: Automated using custom scripts

Data Cleaning: Handling missing values and duplicates

Preprocessing: Standardization and normalization

Feature Engineering with Feast

Feature Store: Managed using Feast

Feature Groups:

Patient Demographics

Medical History

Current Visit Data

Derived Features

Benefits: Consistency, reusability, version control

Model Training and Evaluation

Models Used:

Logistic Regression

AutoGluon (AutoML)

Neural Network

Hyperparameter Tuning: Optuna for optimization

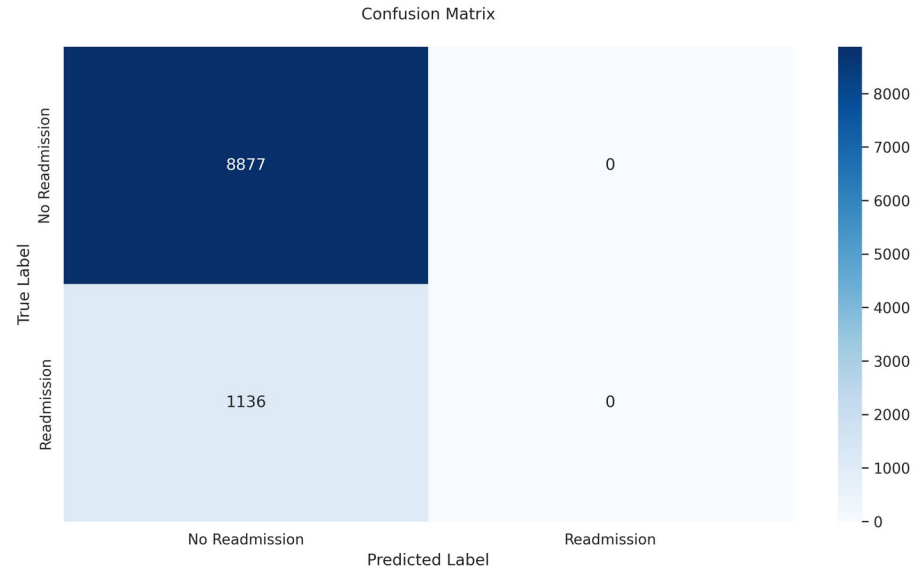
Evaluation Metrics: Accuracy, Precision, Recall, F1-Score, ROC-AUC

Model Performance

Best Model: AutoGluon

Accuracy: 68.30%

ROC-AUC: 72.09%



Model Deployment

Deployment Strategy:

Containerization with Docker

RESTful API using FastAPI

Hosting: Can be deployed on cloud platforms or on-premises

Scalability: Designed for handling varying loads

CI/CD Pipeline

Automation: Implemented with GitHub Actions

Stages:

Code Version Control (Git)

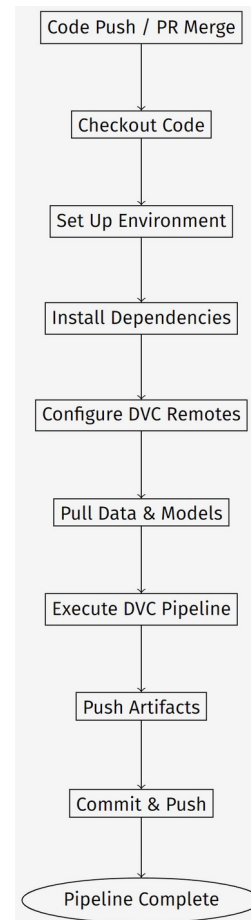
Continuous Integration with Tests

Model Training and Evaluation

Continuous Deployment

Tools: DVC for data and model versioning

CI/CD Pipeline Diagram



Model Monitoring with DVC and DVC Studio

Metrics Tracking: Training loss, accuracy, ROC-AUC

Visualization: DVC Studio dashboards

Alerts: Notifications for performance degradation

Feature Store Monitoring

Data Consistency Checks: Ensuring training and serving data align

Data Drift Detection: Monitoring for shifts in data distributions

Automated Retraining: Triggered when significant drift occurs

Model Registry with DVC

Model Versioning: Managed by DVC

Metadata Tracking: Performance metrics, hyperparameters, dataset versions

Benefits: Traceability, reproducibility, compliance

Batch Inferencing

Use Case: Predicting readmission risk for a batch of patients

Process:

Input: Batch of patient data

Output: Risk scores and categories

Result: Identification of high-risk patients

Infrastructure Monitoring

Monitoring Tools:

GitHub Actions for pipeline
monitoring

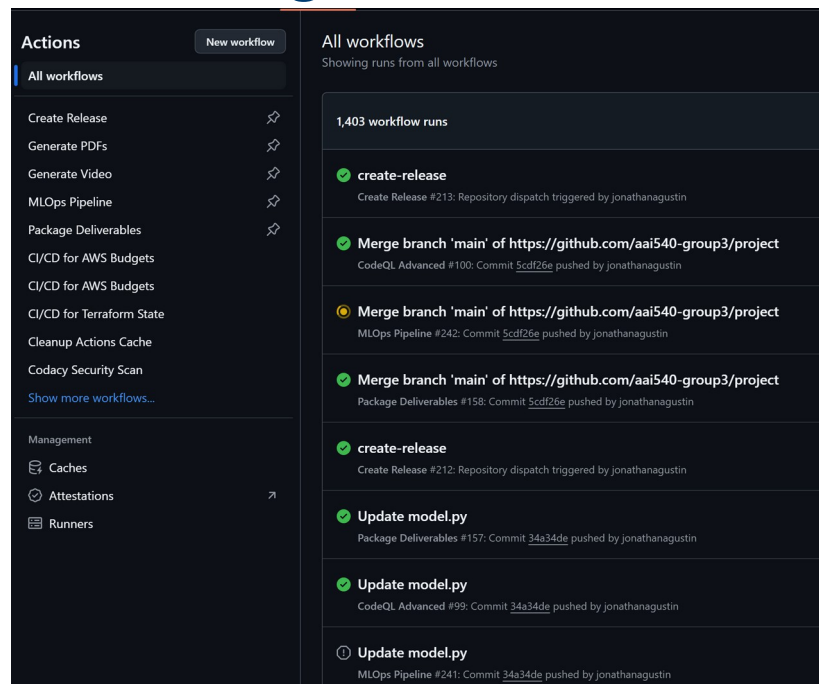
DVC Live for real-time metrics
logging

Key Metrics:

Pipeline execution status

Stage runtimes and logs

Data and model version tracking



The screenshot displays the GitHub Actions dashboard. On the left, the 'Actions' tab is active, showing a list of workflows such as 'Create Release', 'Generate PDFs', 'Generate Video', 'MLOps Pipeline', 'Package Deliverables', 'CI/CD for AWS Budgets', 'CI/CD for Terraform State', 'Cleanup Actions Cache', and 'Codacy Security Scan'. On the right, the 'All workflows' section shows a list of workflow runs. The first run is 'create-release' (Create Release #213), followed by 'Merge branch 'main' of https://github.com/aai540-group3/project' (CodeQL Advanced #100), 'Merge branch 'main' of https://github.com/aai540-group3/project' (MLOps Pipeline #242), 'Merge branch 'main' of https://github.com/aai540-group3/project' (Package Deliverables #158), 'create-release' (Create Release #212), 'Update model.py' (Package Deliverables #157), 'Update model.py' (CodeQL Advanced #99), and 'Update model.py' (MLOps Pipeline #241).

Challenges and Future Improvements

Challenges Faced

Data Imbalance
Ensuring Data Privacy
Scalability Concerns

Future Work

Implementing Explainable AI
techniques
Integrating real-time data sources
Expanding to other chronic
conditions

Ethical and Regulatory Considerations

Data Privacy Compliance: Adhering to HIPAA regulations

Bias Mitigation: Regular audits for fairness across demographics

Transparency: Providing insights into model decision-making

Conclusion

Impact: Enhancing healthcare through predictive analytics

Scalability: Architecture designed for growth

Collaboration: Emphasis on teamwork and continuous improvement

Thank You

Questions and Discussion

File an Issue at our GitHub Repository:
<https://github.com/aai540-group3/project>