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

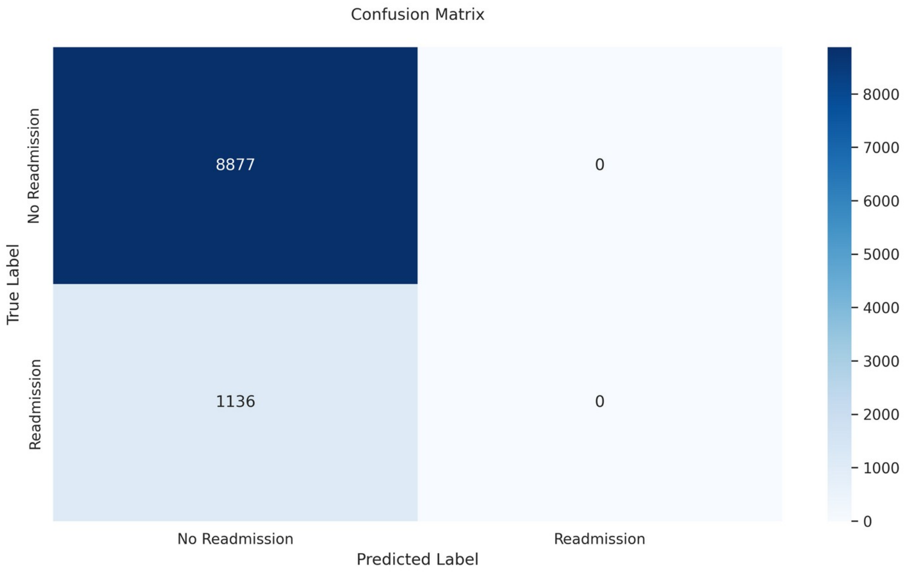
Evaluation Metrics: Accuracy, Precision, Recall, F1-Score, ROC-AUC

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)

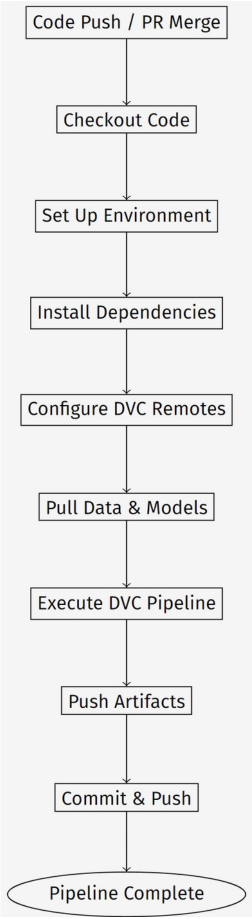
Continuous Integration with Tests

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

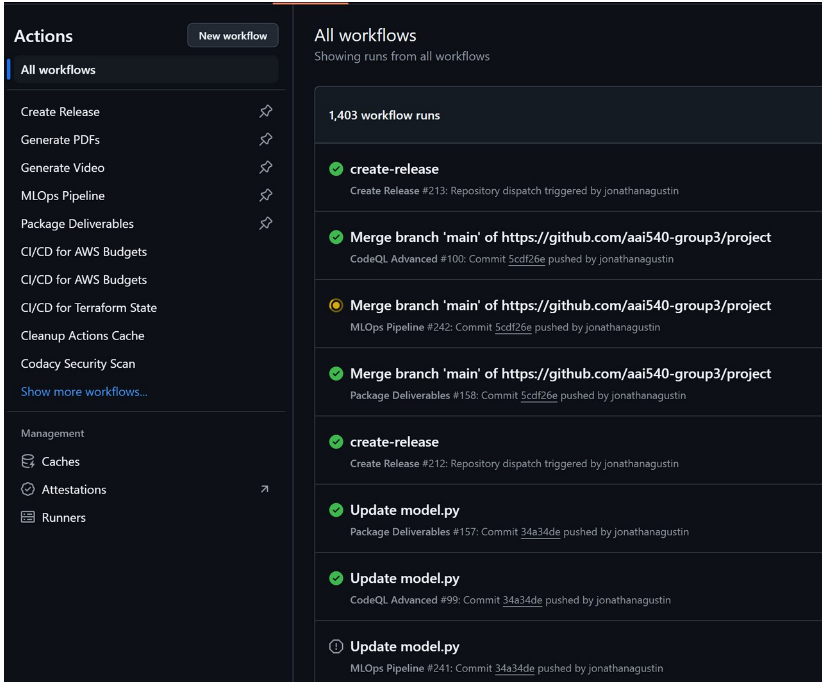
DVC Live for real-time metrics logging

Key Metrics:

Pipeline execution status

Stage runtimes and logs

Data and model version tracking



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