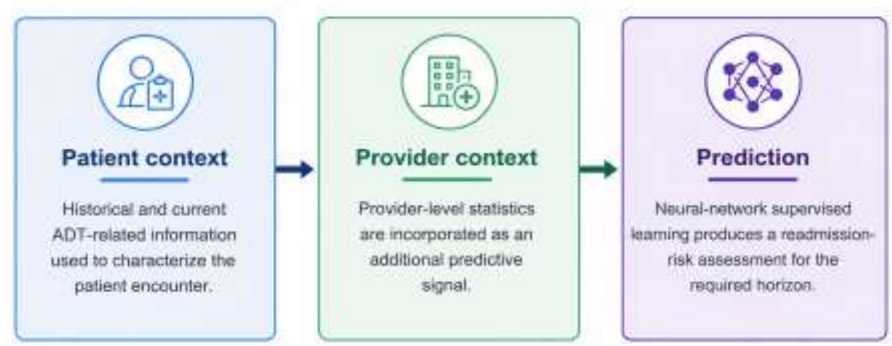
# Predicting Patient Readmission Risk

## Introduction

The solution combines time-based ADT (Admission, Discharge, and Transfer) data with provider data and machine learning to predict patient readmission risk, reducing manual effort and enabling consistent, data-driven assessments. Its core analytical approach uses supervised learning with a neural-network model to assess readmission risk across multiple time horizons. In addition to predicting 90-day readmission risk, the solution provides insights for 30-day and 60-day periods, enabling a more nuanced, multi-horizon assessment rather than relying on a single binary outcome.




## Client Details

**Name:** Confidential | **Industry:** Healthcare | **Location:** USA

## Technologies

Programming Language: Python
Framework: Keras / TensorFlow
Learning Type: Supervised Learning
Model: Neural Network
Data Format: CSV

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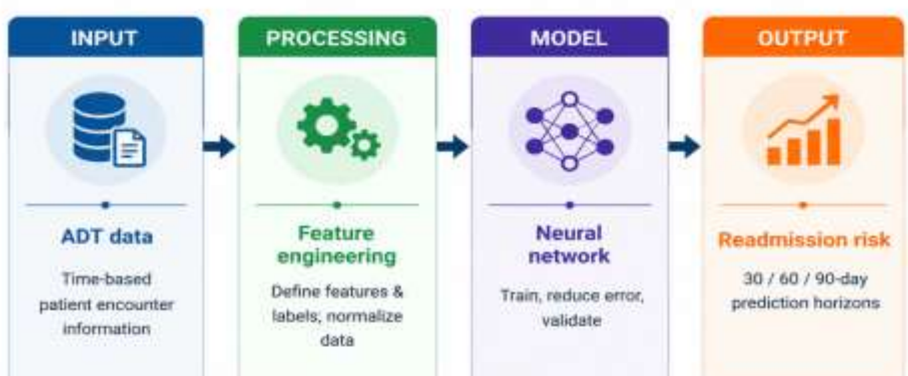
## Project Description:

### Business Challenges

- Manual Assessment
    - Time-consuming evaluation of patient and provider information.
- Data Complexity
    - Combining time-based ADT data with provider statistics.
- Inconsistent Evaluation
    - Lack of a standardized, repeatable risk-assessment process.
- Limited Risk Visibility
    - Need to assess readmission risk across 30, 60, and 90-day horizons.
- Decision Support Gap
    - Need for data-driven insights to support care-management decisions.

### Functional View

The proposed capability converts historical healthcare data into a repeatable prediction workflow. Instead of relying on a manually assembled risk assessment, the system prepares the data, trains a supervised model, evaluates it, and applies the trained model to test data.



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**Primary Stakeholders**

- **Care / Clinical Teams:** Use risk information to support patient-management decisions.
- **Provider / Operations Teams:** Understand how provider-level patterns influence predictions.
- **Analytics / ML Teams:** Maintain training, validation, and model-performance processes.
- **Healthcare Leadership:** Use aggregated risk insights to identify opportunities to reduce avoidable readmissions.

**Model Development and Evaluation**

The workflow separates data preparation from model development and prediction. This separation supports a repeatable model lifecycle in which preprocessing is applied before training, the data is split for evaluation, and the trained model is ultimately exercised against a test dataset.

| Data preparation | Training | Validation | Testing |
|---|---|---|---|
| Read CSV Define features & labels Normalize | Train neural network Reduce error | Hold-out validation data Monitor generalization | Predict on test dataset Assess behavior |

**Risk Horizons**

| 30 Days | 60 Days | 90 Days |
|---|---|---|
| Near-term readmission risk horizon | Intermediate readmission risk horizon | Longer-term readmission risk horizon |

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## Workflow:

A repeatable prediction workflow based on the source deck: ingest the prepared data, prepare features, predict, and review the resulting risk output.


**Operational workflow for readmission-risk prediction**

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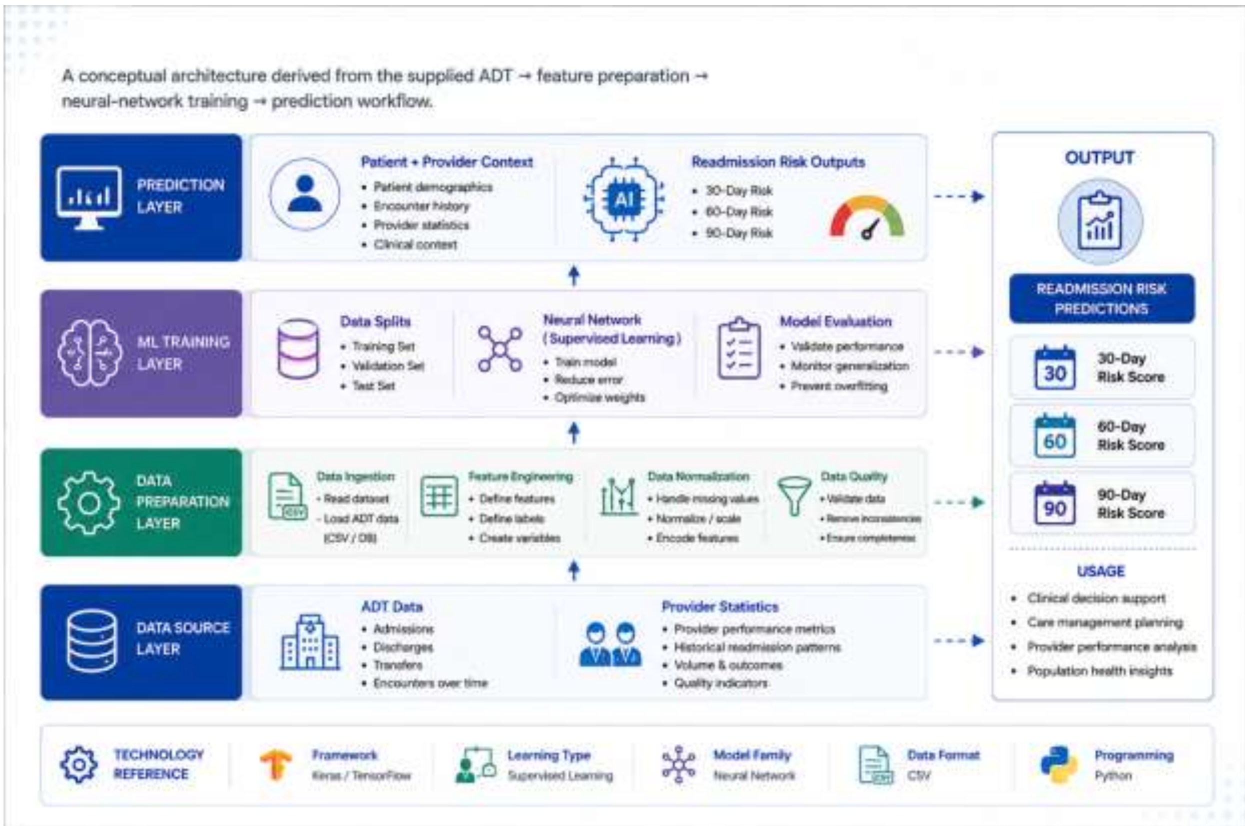
## Architecture:

A conceptual architecture derived directly from the supplied ADT → feature preparation → neural-network training → prediction workflow.




**Data processing and machine-learning pipeline**

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## Benefits:

- **Reduced manual effort:** Automates a data-driven readmission-risk prediction workflow.
- **Consistent methodology:** Applies a defined feature, normalization, training and prediction pipeline.
- **Multi-horizon view:** Supports the 30-, 60-, and 90-day risk horizons shown in the reference.
- **Patient + provider context:** Uses both time-based ADT information and provider statistics.
- **ML-driven approach:** Uses supervised learning with a neural-network model.

## Data, Governance and Clinical Considerations:

- **Source-established:** The solution uses patient-related ADT data and provider statistics for prediction, with a supervised neural-network approach.
- **Should be addressed in production:** Access control, protection of patient data, auditability, model governance, dataset lineage, monitoring, validation, and appropriate clinical-use controls.
- **Important model principle:** A risk prediction should support, and not replace clinical judgment. Model outputs should be evaluated for accuracy, calibration, bias, drift, and appropriate use before operational adoption.

## Conclusion:

The solution for Predicting Patient Readmission Risk applies supervised machine learning and a neural-network approach to time-based ADT data and provider statistics. The workflow involves ingesting the dataset, defining features and labels, normalizing the data, creating training, test, and validation sets, training the model to minimize prediction error, and generating predictions on test data. The solution evaluates readmission risk across 30, 60, and 90-day horizons, with 90-day readmission risk identified as a key impact target.