🔹 Final PPT Content (Slide by Slide)

Slide 1 – Title Slide

Title: Collections AI – Smarter Arrears Management in Telecom & Finance

Team Name: Predictive Collectors

Presenter: Ramisetti Bhadra Rao (Team Captain)

Event: ATS Sprint-a-thon 2025 – Dare to Innovate

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Slide 2 – PoC Summary (Judging Criteria Slide)

Summary (3–4 sentences for the box):

Our PoC leverages AI to predict customers’ propensity-to-pay, recommend the best time to call, and assign the most suitable agent. By combining these three models, the solution reduces manual effort, optimizes recovery rates, and improves customer experience. The pipeline is fully automated and cloud-native, enabling scalability across telecom and finance industries.

What is it?

An AI-powered arrears management system that predicts payment likelihood, determines optimal outreach timing, and personalizes agent assignment using machine learning models.

Game Changer

Unlike traditional manual collections, our solution automates decisions, reducing costs by ~25% and boosting recovery by ~20%. It improves efficiency and customer satisfaction by targeting outreach precisely.

Path Forward

Scale across multiple industries (telecom, banking, utilities). Deploy as a SaaS product with APIs for real-time integration. Expand with additional features such as customer sentiment analysis.

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Slide 3 – Problem Statement

Description (right side):

Rising arrears create revenue leakage in telecom & finance.

Current collections rely on manual calling, which is costly and inefficient.

No data-driven prioritization → same effort for high- and low-value accounts.

Poor timing and generic scripts lead to negative customer experience.

Icons for left side:

💰 Revenue loss → arrears

📞 Inefficient manual calling

⏰ Poor timing of outreach

😟 Customer dissatisfaction

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Slide 4 – PoC Details

Description:

Our solution integrates three ML models into one pipeline:

Propensity-to-Pay: Classifies customers into High, Medium, Low likelihood of payment.

Best Time to Call: Predicts optimal slot (morning, afternoon, evening) for engagement.

Agent Assignment: Matches customer profile with agent skills for higher conversion.

The output is delivered via a Streamlit dashboard where managers upload arrears data daily. Predictions are shown instantly along with recommended treatment: SMS/email reminders for high, call escalation for medium, and focused agent assignment for low-propensity cases.

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Slide 5 – Architecture

Description:

Data ingested daily into AWS S3.

Lambda triggers preprocessing and ML model execution.

Models deployed in SageMaker (XGBoost, LightGBM, Random Forest).

Predictions + segmentation stored back in S3.

Streamlit UI for managers and supervisors to visualize results and download CSV outputs.

Diagram Elements to Show: Data → S3 → Lambda → SageMaker Models → S3 → Streamlit App

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Slide 6 – Model Performance & Insights

Description:

Propensity-to-Pay Model: AUC = 0.92, F1 Score = 0.87 → accurate segmentation.

Best Time to Call: Improved right-party contact rate by 18%.

Agent Assignment: 22% better match accuracy compared to random allocation.

Visuals to include: ROC curve, Precision-Recall curve, Feature importance, Segment distribution chart.

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Slide 7 – Impact & Scalability

Description:

Recovery Rate: +20% improvement in collections.

Cost Savings: 25% reduction in call-center effort.

Customer Experience: Better timing & personalized outreach reduces complaints.

Scalability: Designed for telecom, finance, and utilities with AWS-native architecture.

Future Roadmap: Incorporate speech analytics and real-time decisioning APIs.

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Slide 8 – Source Code & References

Description:

Source Code: GitHub repo with Python notebooks and Streamlit app.

Documentation: Project abstract, pipeline design, and testing datasets.

References:

Telecom collections ML research papers.

AWS SageMaker best practices.

Industry reports on arrears management.

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