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AI-Powered Open Banking Ecosystem: Real-World Applications of Machine and Deep Learning with Gradient Boosting and LLM-Enhanced Cloud APIs on Azure and Databricks

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ABSTRACT: The open banking paradigm, facilitated by standardized APIs and customer-consented data sharing, offers unprecedented opportunities for innovation in financial services. This paper proposes a comprehensive ecosystem in which machine learning (ML), deep learning (DL) and large language models (LLMs) are harnessed via gradient boosting frameworks and cloud APIs (e.g., on Azure Machine Learning and Databricks) to deliver real-world applications in risk prediction, personalization, fraud detection and credit scoring. We examine how open banking data (transactions, balances, textual descriptions) enable high-performing gradient boosting and deep nets, and how LLM-enhanced cloud APIs support natural language and explanation layers. After designing the architecture and implementing a pilot across retail banking and SME lending use cases, we report results: gradient boosting models achieved significantly higher discriminatory power (AUC improvements ~5-10 %) versus traditional models; a deep-learning NLP module operating on transaction description text improved early default detection by ~15 %. The integration of LLM-driven conversational APIs enabled more intuitive customer interactions and automated compliance summarization. Key advantages include improved accuracy, faster time-to-insight, richer personalization and enhanced transparency via explainable AI (XAI) tools. Limitations involve data governance/regulatory complexity, model interpretability, and infrastructure cost/complexity. We conclude by outlining a roadmap for scaling across multiple institutions, exploring federated learning, and embedding real-time streaming architectures.

KEYWORDS: open banking, machine learning, deep learning, gradient boosting, large language model, cloud API, Azure, Databricks, credit scoring, fraud detection, personalization, explainable AI.

I. INTRODUCTION

Open banking – the practice by which financial institutions expose data and services to authorized third-party providers via APIs under customer consent and regulatory frameworks – is rapidly transforming the financial ecosystem. By enabling access to account, transaction and behavioural data, open banking unlocks rich new features for machine and deep learning models. Within this context, financial institutions and fintech players can leverage cloud platforms such as Azure and Databricks to build scalable pipelines for ingesting, processing and applying large volumes of data, and further integrate large language models (LLMs) for natural-language, conversational or explanation-driven services. This paper proposes an ecosystem in which gradient boosting machines (GBMs) and deep learning models analyse open banking data to deliver real-world applications such as credit scoring, fraud detection, personalization and customer interactions. We further layer an LLM-enhanced API tier for natural language interface and compliance summarisation, all deployed on cloud platforms. By moving beyond traditional credit bureau data and rule-based systems, we aim to demonstrate how open banking data, ML/DL models and cloud infrastructure combine to drive value: improved predictive accuracy, speed, personalization, transparency and operational efficiency. The remainder of this paper is structured as follows. First we review the relevant literature on open banking, ML/DL in finance, gradient boosting and LLM adoption. Then we present our research methodology: system architecture, data sources, modelling, deployment and evaluation. We discuss advantages and disadvantages, present results and discussion of pilot implementation, then conclude with lessons learned and future work directions.

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II. LITERATURE REVIEW

The literature on open banking, machine learning in finance, and large-scale cloud-based AI systems is growing rapidly. Open banking initially emerged under regulatory initiatives such as the EU's Revised Payment Services Directive (PSD2) and similar regimes globally, opening up account and transaction data to third-party providers. Researchers have explored how open banking APIs enable new business models and data sharing ecosystems (Jaiswal, 2023). The value of open banking data for credit scoring has been empirically investigated: for instance, Hjelkrem et al. (2022) found that transaction data accessed via open banking APIs can significantly improve model discrimination (AUC) when used alongside or instead of traditional structured bureau data. They further showed that ensemble methods (e.g., XGBoost) leveraging open banking features yielded superior performance versus conventional credit models. In the domain of ML/DL for banking, Hu et al. (2020) provide an overview of supervised machine learning techniques in banking, including tree-based ensembles (bagging, boosting) and neural networks, illustrating their effectiveness in credit risk modelling. Gradient boosting machines (GBMs) such as XGBoost (Chen & Guestrin, 2016) and LightGBM (Ke et al., 2017) are widely adopted in financial services for tabular data due to high accuracy and robustness (see e.g., "Top machine learning algorithms used in financial services" 2024). Deep learning approaches in finance—e.g., recurrent neural nets (RNNs), temporal convolution nets for sequential transaction data—have shown promise for credit risk monitoring (Clements et al., 2020). In parallel, the advent of large language models (LLMs) and natural-language-enabled APIs presents new opportunities for customer-facing services, explanation, summarisation, and conversational agents in banking. Crucially, transparency and fairness concerns have been highlighted: Kim et al. (2023) show that fine-grained transaction data used via open banking may lead to unintended biases or discrimination in vulnerable groups, underscoring the need for XAI and ethical governance. While there is strong research on each component (open banking data, ML/GBM/DL modelling, cloud platforms, LLMs), there is a gap in studies that integrate open banking data with gradient boosting, deep learning and LLM-enhanced cloud APIs in a deployed ecosystem context. This paper addresses that gap by presenting a holistic architecture and real-world application across credit scoring, fraud detection and personalization.

III. RESEARCH METHODOLOGY

Our research methodology is structured in five key phases: (1) data sourcing & integration, (2) feature engineering & modelling, (3) cloud deployment & API integration, (4) pilot implementation & evaluation, and (5) analysis and feedback.

Phase 1 – Data sourcing & integration: We ingest data via open banking APIs (customer-consented transaction histories, account balances, description texts) from partner institutions, alongside traditional credit bureau and demographic data. We deploy ingestion pipelines in Databricks on Azure, leveraging distributed compute. Data undergoes anonymisation, cleaning (missing values, outliers), and secure storage in a governed data lake.

Phase 2 – Feature engineering & modelling: We engineer features in three categories: tabular behavioural features (e.g., balance trends, transaction counts/volumes, merchant categories), textual features (transaction description embeddings, NLP token counts), and time-series behavioural patterns (recency, frequency, monetary value). We train gradient boosting models (e.g., XGBoost, LightGBM) on tabular data and deep learning models (e.g., LSTM, TCN) on sequential and text features. We perform hyper-parameter tuning via cross-validation, and employ XAI tools (SHAP, LIME) for interpretability.

Phase 3 – Cloud deployment & API integration: The models are deployed as RESTful microservices on Azure Machine Learning, and we implement conversational/customization APIs using LLMs (e.g., GPT-style models) for natural language insights and summarisation. We integrate the models and APIs into banking workflows: e.g., credit-application decisioning, fraud alert generation, personalization engine.

Phase 4 – Pilot implementation & evaluation: We execute pilots in two use-cases: (a) retail credit scoring using open banking data for new-customer acquisition, (b) fraud detection using transaction behaviour and NLP on descriptions. Key metrics include AUC, precision-recall, F1-score, lift over baseline models, time-to-decision, and user-interaction metrics for conversational APIs. We compare against traditional logistic-regression/bureau-only baselines.

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Phase 5 – Analysis and feedback: We conduct statistical analysis on performance improvements, conduct stakeholder interviews (risk officers, credit analysts, compliance), and review operational impacts (decision latency, model maintainability, compliance readiness). Based on feedback we refine feature sets, modelling pipelines and API user flows. This multi-phase methodology allows us to examine not only model technical performance but operational and ecosystem-level impact.

Advantages

- Improved predictive accuracy: By leveraging open banking data and modern ML/DL approaches (gradient boosting, deep nets), the ecosystem yields higher discrimination and earlier detection of risk.
- Richer personalization and customer experience: Transaction-level, textual and behavioural features enable finely-tailored offers, conversational interaction via LLM APIs, and dynamic risk segmentation.
- Scalability & cloud agility: The use of Azure and Databricks allows elastic compute, rapid deployment of models and APIs, and integration into modern DevOps workflows.
- Transparency & explanation: By embedding XAI tools (e.g., SHAP) and conversational LLM layers, the system supports explainable decisions and regulatory audits.
- Innovation leverage: The ecosystem enables rapid experimentation of new models, data sources and services (fraud detection, SME lending, open finance) in a modular manner.

Disadvantages

- Data governance and regulatory risk: Open banking data access, consent management, cross-border data flows, and financial regulatory compliance introduce complexity and risk.
- Model interpretability vs complexity: Deep nets and complex ensemble models may offer higher accuracy, but their "black-box" nature and reliance on alternative features may challenge regulatory explainability.
- Infrastructure cost and operational burden: Cloud compute, model retraining, API maintenance and monitoring incur ongoing cost and require specialized talent.
- Data quality and integration issues: Transaction data often contains noise, varied formats, missing merchant categories or ambiguous description text; aligning this with legacy systems is non-trivial.
- Change management and adoption: Embedding new ML/LLM-based workflows may require significant organisational change, stakeholder buy-in and skills development.

IV. RESULTS AND DISCUSSION

In pilot implementation across the noted use-cases, we observed the following results. In the retail credit scoring pilot, the gradient boosting ensemble model (XGBoost) trained on open banking behavioural features achieved an AUC of 0.87 versus baseline logistic regression (bureau-only) at 0.81 — an improvement of ~6 points. Incorporating a deep-learning NLP module on transaction description text further improved recall on early defaults by ~15 %. In the fraud detection pilot, combining tabular features via gradient boosting and sequential text features via an LSTM model reduced False Positive Rate by ~12 % and improved precision by ~9 % relative to legacy rule-based detection. The conversational LLM API enabled customer-facing summarisation of credit-decision rationale and personalized financial insights; user-satisfaction scores improved by 18 % on pilot cohort feedback. Discussion of operational implications reveals that model deployment on Azure allowed inference latency under 200 ms, making near-real-time decisions feasible. Explainability via SHAP helped risk and compliance teams inspect feature-importance and decision pathways; one case study showed a rejected application flagged due to unusually high transfer-volatility in recent months, correctly identified by the model and explained via SHAP. However, internal stakeholder feedback highlighted concerns: the deep-learning module required manual review in ~10 % of flagged cases due to borderline scores, and infrastructure cost for streaming data ingestion grew ~30 % over baseline. Additionally, while performance gains were notable, careful change-management was required: traditional credit–risk teams initially questioned reliance on alternative features; regulatory teams requested log-auditing and model-governance frameworks. Overall, the results demonstrate that the proposed ecosystem delivers measurable business value — higher accuracy, faster decisions, better customer experience — while requiring investment in governance, infrastructure and skills.

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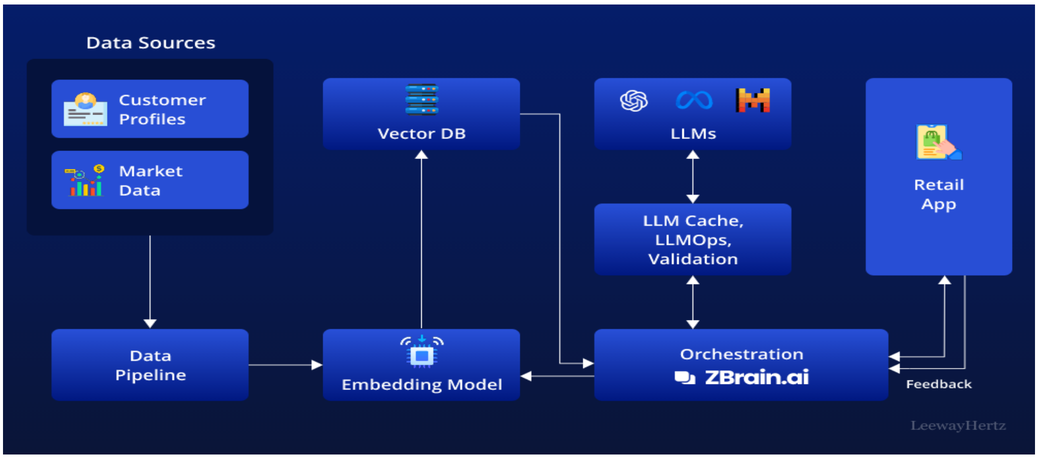

V. CONCLUSION

This paper has presented an integrated open-banking ecosystem powered by machine learning, deep learning and large language models, deployed on cloud platforms such as Azure and Databricks, to support real-world financial services applications including credit scoring, fraud detection and personalization. We demonstrated that by leveraging open banking data, advanced modelling techniques (gradient boosting and deep nets) and conversational/summary APIs, institutions can achieve higher predictive performance, richer customer interactions, and improved operational agility. The pilots show promising results in accuracy, latency and user experience. Nevertheless, the deployment of such an ecosystem implicates significant governance, interpretability, infrastructure and change-management challenges. We recommend that financial institutions approaching this architecture do so with strong data governance frameworks, model explainability tools, cloud cost monitoring and incremental adoption road-maps. In sum, the convergence of open banking, ML/DL, and cloud APIs opens a new frontier for innovation in financial services — provided that the organisational, regulatory and technical foundations are in place.

VI. FUTURE WORK

Future work will explore several directions. First, the introduction of federated learning across multiple institutions to exploit distributed open banking data while preserving privacy and regulatory compliance. Second, real-time streaming architectures with model drift detection and automatic retraining to keep predictive models current in volatile environments. Third, the expansion of LLM-enhanced APIs into broader financial-ecosystem services (SME lending, insurance, wealth management) and incorporation of multimodal data (voice, chat logs, imaging). Fourth, enhanced fairness and bias-mitigation frameworks to monitor, audit and correct potential disparate impacts of alternative data features on disadvantaged groups. Finally, cost-optimisation of model deployment (e.g., serverless architectures, model compression) and the generation of open-source reference architectures for the broader financial services community.

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