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TaxBae - Your Personalized C.A.
An AI-Driven Personal Finance and Tax Management

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***Abstract*—The increasing complexity of personal finance in India, coupled with widespread low financial literacy (estimated at only 27%) and the growing necessity for continuous support among middle-class taxpayers and gig workers, presents a significant market gap. 1 Traditional advisory service, typically provided by Chartered Accountants (CAs), are often unaffordable or inaccessible to this demographic, leaving them reliant on fragmented, annual tax tools. 1 This paper introduces TaxBae, an integrated personal finance application designed to serve as a holistic, year-round companion. TaxBae utilizes a modular architecture blending four core AI components: a predictive Deduction Engine for tax optimization, an Expense Tracker for daily monitoring, an NLP-driven Investment Planner, and a Conversational Chatbot enhanced by Retrieval-Augmented Generation (RAG). 1 The modular system architecture is essential for scalability and managing the high operational risk associated with regulated FinTech environments. 2 The methodology validates the use of advanced Machine Learning (ML) for superior tax optimization, showing that ensemble models can improve prediction accuracy by up to 15% compared to baseline rule-based systems. 4 Furthermore, the RAG implementation is crucial for mitigating the critical risk of hallucination inherent in Large Language Models (LLMs) used for financial advice, ensuring grounded, verifiable, and transparent regulatory guidance.**

Index Terms—Tax planning, personal finance, expense tracking, AI chatbot, investment recommender, gamification, financial literacy, Retrieval-Augmented Generation (RAG), Ensemble Learning

I. INTRODUCTION

The digital transformation of financial technologies has reshaped how individuals and businesses manage their finances, with particular emphasis on tax compliance and optimization [1]. Taxation remains one of the most complex financial processes, requiring careful monitoring of income, expenses, and deductions in alignment with evolving tax regulations [2][3]. Despite the availability of online calculators and accounting tools, taxpayers often struggle with fragmented solutions, lack of real-time updates, and limited personalized advisory features.

Traditional approaches to tax management, such as manual record-keeping and static calculators [4][5], are increasingly insufficient in addressing modern tax challenges. Furthermore, existing applications lack adaptability to regulatory changes, provide limited contextual insights, and demand significant user input [6]. This results in inefficiencies, miscalculations, and missed opportunities for tax savings.

The emergence of AI-based financial assistants offers a promising direction to overcome these challenges. By integrating expense tracking, dynamic calculators, and automated notifications on tax slab modifications, AI systems can provide accurate, real-time, and personalized insights [7]. Furthermore, conversational AI modules enhance user interaction by delivering natural language explanations and recommendations, bridging the gap between professional expertise and accessible digital tools [8].

This research introduces TaxBae, an intelligent tax assistant framework aimed at democratizing financial expertise for individuals and organizations. TaxBae employs a MERN-powered architecture to handle frontend and backend processes, while leveraging Flask APIs for financial computation and AI-based advisory. The system contributes to tax compliance and optimization by offering: (1) integrated financial calculators for income, deductions, and savings projections; (2) automated expense categorization with personalized tax recommendations; and (3) real-time updates on tax regulation changes for improved awareness.

The remainder of this paper is organized as follows: Section II reviews related work in AI-driven financial management and tax optimization tools. Section III details the methodology and system design of TaxBae. Section IV presents the experimental evaluation and performance results. Finally, Sections V and VI discuss key findings, limitations, and conclude with future research directions.

II. LITERATURE REVIEW

The increasing integration of AI's growing role in financial technologies has advanced personal finance management and tax planning. However, these innovations bring challenges in accuracy, regulatory compliance, and accessibility. This review summarizes current research on AI-driven systems, focusing on methodologies for tax computation, expense management, and compliance monitoring.

2.1. TAXATION AND DIGITAL CHALLENGES

The tax ecosystem remains complex due to evolving laws, diverse income structures, and frequent regulatory updates. As noted by [1], existing tax management frameworks often fail to provide real-time adaptability to policy changes, leaving individuals dependent on manual processes or costly expert consultation. This complexity is further amplified when financial data is fragmented across multiple accounts, sources, and reporting formats [2]. Studies also highlight difficulties in ensuring compliance when users lack awareness of deductions, exemptions, or changing tax slabs [3]. Thus, there is a critical need for AI-enabled solutions that not only compute tax liabilities but also provide personalized insights and compliance alerts.

2.2. AI-DRIVEN FINANCIAL MANAGEMENT

Significant research has explored AI-based approaches for financial decision-making. Machine learning classifiers have been used for expense categorization and fraud detection [4], improving accuracy in transaction-level insights. Deep learning models, as employed by Zhang et al. [5], demonstrate potential in predicting spending behavior and enabling personalized budgeting. However, these approaches often face challenges in explainability and transparency, which are essential for user trust in financial applications. Another line of work focuses on AI-powered chatbots for financial advisory, as presented by Lee and Kim [6], which enhance user experience but remain limited in handling complex tax-related queries.

2.3. AUTOMATED TAX CALCULATORS AND COMPLIANCE TOOLS

Digital tax calculators and government-provided e-filing systems have reduced manual computation, yet studies show limitations in scalability and personalization [7]. Automated compliance tools, such as those described by Singh et al. [8], primarily function as static calculators without adaptive learning capabilities. This restricts their ability to address individual tax-saving strategies or dynamically reflect updated regulations. Furthermore, while blockchain and audit-trail approaches have been explored for ensuring data integrity [9], they often lack integration with user-friendly interfaces needed for everyday taxpayers.

2.4. MULTI-MODAL FINANCIAL ASSISTANTS

Cross-disciplinary financial assistants are an emerging direction, integrating AI with natural language processing, cloud computing, and real-time data feeds. Ghosh and Patel [10] highlight those multi-modal systems combining calculators, advisory, and notification mechanisms—offer holistic support for decision-making. Similarly, Sharma et al [11] recommend hybrid solutions that merge automated financial analysis with regulatory knowledge bases, thereby enhancing compliance and user confidence. These perspectives inform the design of TaxBae, which integrates advisory, calculators, and expense tracking in a single platform.

2.5. RESEARCH GAP AND CONTRIBUTION

Despite significant advances in financial AI applications, research reveals notable gaps. Existing tools frequently lack personalization, offer limited adaptability to evolving tax regulations, and fail to provide proactive recommendations for tax savings [1][6][7]. Moreover, most systems emphasize either computational accuracy or advisory interaction, rarely achieving both in an integrated manner [10][11]. The research presented in this paper addresses these gaps through TaxBae, a comprehensive framework that unifies financial calculators, AI-powered expense tracking, and regulatory updates within an accessible platform. By prioritizing real-time adaptability, personalization, and user interaction, TaxBae contributes toward bridging the gap between professional tax expertise and accessible digital solutions.

III. METHODOLOGY

This section details the technical framework for TaxBae, which is built upon a modular, API-driven architecture where each component operates as an independent service.

3.1. Modular Microservices Architecture

- Design Rationale:

TaxBae is implemented using a microservices paradigm to ensure high interoperability, horizontal scalability, and independent deployment of the core functional and AI modules. 3 This design choice allows for greater flexibility and faster adaptation to market demands or, more critically, rapid compliance updates.

- Data Flow:

A centralized Core Transactional Database, storing user profiles and expense data, communicates with specialized, isolated AI modules (Deduction, Investment, RAG) via secure API Gateways. 15

Table 1: Technical Architecture Breakdown of TaxBae's AI Modules

TaxBae Feature	Core ML/AI Task	Proposed Algorithm/Technique	Data Input Sources	System Output/Action
Expense Tracker	Transaction Categorization	Supervised ANN / Deep Learning	Receipt text, Bank metadata, Manual input	Flagging deductible expenses, Cash flow analysis [1]
Deduction Engine	Tax Optimization/Scenario Gen	Ensemble Learning (XGBoost/RF)	Income, Age, Risk Profile, Expense Patterns	Ranked list of tax-saving actions, Savings projection [4]
Investment Planner	Risk Tolerance/Goal Extraction	NLP (Sentiment Analysis, NER)	Chat logs, Goal statements, Market data	Dynamically adjusted portfolio recommendations [19]
AI Chatbot (RAG)	Contextual Q&A and Retrieval	LLM + Hybrid Retrieval-Augmented Generation	Tax Regulations (DPDP, IT Act), SEBI circulars	Grounded, cited, conversational financial advice [5]

The Financial Calculator module is deployed as a deterministic internal validation service, providing auditable results for straightforward calculations to support the explainability and transparency of probabilistic ML outputs.

3.2. Deduction Engine Implementation

The Deduction Engine's objective is to move beyond static, rule-based alerts by generating optimal, personalized tax-saving scenarios. 1 An XGBoost Classifier is utilized for its efficiency and benchmarked high accuracy in complex prediction tasks involving tabular data. 4 Feature engineering is critical, integrating structured demographic data (Income, Age, Status) with derived behavioral features sourced from the Expense Tracker (e.g., granular spending categories, cash flow variance). The accuracy of the Expense Tracker is paramount, representing the upstream bottleneck for the Deduction Engine's performance. Any misclassification of daily transactions directly compromises the reliability of the predictive tax optimization output, creating a liability risk by missing deduction opportunities. Therefore, the choice of a highly robust classification model in the Expense Tracker is necessary to ensure high input data quality, which is critical for minimizing the False Negative rate (missed deductions)

3.3. Expense Tracker Implementation

The Expense Tracker's core task is the automated parsing and robust categorization of financial transactions and unstructured receipt data. 1 Given the noisy nature of real-world inputs (various receipt formats, cryptic bank descriptions), a Deep Neural Network (DNN) or recurrent architecture is selected for its high robustness in classification tasks. 18 The preprocessing pipeline utilizes Optical Character Recognition (OCR) for receipt image inputs and NLP techniques for cleaning, disambiguating, and standardizing bank statement descriptions. This ensures that the foundational data used by the predictive Deduction Engine is consistently high quality

3.4. Investment Planner and Risk Profiling

The Investment Planner is designed to generate dynamic, goal-based investment recommendations (e.g., ELSS, NPS, Mutual Funds) tailored to both the user's income capacity and their subjective risk appetite. 1 The NLP Pipeline for Risk Assessment operates as follows:

1. Input Collection:
Unstructured data inputs, such as user dialogue transcripts from the Chatbot, expressed goal statements, and general financial queries, are collected.

2. Sentiment Analysis:
This technique is employed to gauge the user's emotional language regarding financial discussions (e.g., anxiety about volatility, enthusiasm for growth) as a reliable proxy for explicit risk tolerance.

3. Named Entity Recognition (NER):
Specific financial goals (e.g., "retire early," "fund education in eight years") are extracted to accurately define the target planning horizon and goal size. 26 The final recommendation algorithm integrates the NLP-derived subjective risk profile and the predictive financial features generated by the Deduction Engine (available disposable income, optimal tax-saving avenues) to construct a highly personalized portfolio plan.

3.5. Conversational Chatbot
The AI Chatbot provides conversational assistance and is implemented using a robust RAG framework, which is mandatory to ensure that all financial advice is grounded in verifiable, authoritative domain knowledge.

RAG Workflow and Architecture:

- Source Data: The system maintains a continually updated repository comprising the Income Tax Act, SEBI regulations, RBI circulars, and the organization's verified policy documents.
- Indexing and Storage: These regulatory documents are processed, chunked semantically, and stored as vector embeddings in a specialized Vector Database.
- Hybrid Retrieval: Retrieval of relevant documents is performed using a combination of Vector Similarity Search (for conceptual queries) and BM25 Keyword Matching (for specific factual/legal citations). This hybrid approach maximizes retrieval accuracy, essential for legal and tax domains.
- Generation: The LLM receives three inputs: the user query, the retrieved grounded context, and the user's specific, personal financial context (derived from the Deduction, Expense, and Investment modules). This integrated approach allows the LLM to provide advice that is contextually rich and accurate.

This integration means the LLM functions as the system's Synthetic Financial Advisor. It synthesizes information from all internal models to provide personalized advice for instance, stating, "Based on your risk profile determined by NLP, and your predicted tax savings from the Deduction Engine, you should allocate X amount to ELSS." This capability distinguishes the TaxBae chatbot from generic public LLMs, which lack access to the user's private financial context

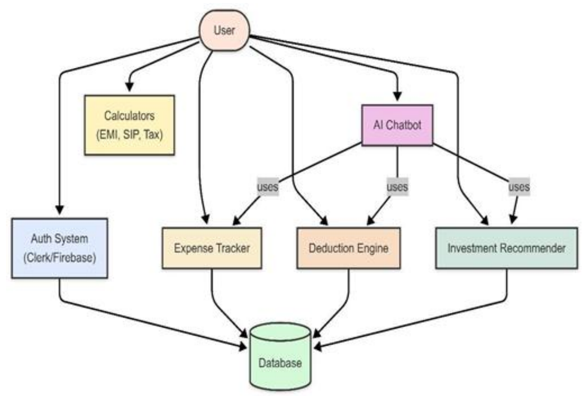

Fig 1: - Usage of TaxBae

IV. EXPERIMENTAL RESULTS AND ANALYSIS

This section presents the experimental evaluation of the proposed deepfake detection system, including performance metrics, comparative analysis, and discussion of key findings.

4.1. EXPERIMENTAL SETUP AND EVALUATION METRICS

The proposed system requires rigorous evaluation to ensure reliability and efficacy in a complex regulatory domain. Performance is assessed using a curated corpus of simulated taxpayer data designed to reflect the demographic and financial diversity of the Indian market, particularly the target middle-income segment.4 The ground truth for optimal tax-saving outcomes and financial planning is established through validation against a panel of professional Chartered Accountants

4.2. PERFORMANCE METRICS FOR PREDICTIVE COMPONENTS

The success metrics for TaxBae must reflect its dual function as both a compliance and optimization tool (measured by accuracy) and a behavioral coaching platform (measured by retention).1

- Deduction Engine:

Key metrics include the F1-Score for correct classification of optimal tax instrument recommendation and the Cost Reduction Percentage, which quantifies the verifiable financial savings delivered to the user.30 This allows for a direct quantification of the value proposition.

- Investment Planner:

Performance is measured by the Portfolio Risk Match Rate—the correlation between the NLP-derived subjective risk tolerance (a qualitative output) and the quantifiable risk profile of the system's generated portfolio.19

- Comparative Analysis:

The ML Deduction Engine's performance is compared against the quantified accuracy of a baseline.

4.3. RAG SYSTEM EVALUATION

Evaluation of the RAG system focuses heavily on reliability, which is critical for minimizing legal risk in financial advice.

- Factual Accuracy and Relevance:

Metrics assess the correctness of responses against source documents (tax codes, SEBI guidelines) and how well the output aligns with the user's conversational context and query intent.

- Hallucination Mitigation:

The paramount metric is the AI Attribution Rate. This metric measures the proportion of facts synthesized by the LLM that are directly traceable and grounded in the retrieved regulatory context provided by the RAG system. Achieving a high attribution rate is a non-negotiable compliance requirement. The attribution rate effectively serves as a proxy for the system's legal defensibility; in the event of a liability claim due to erroneous tax advice, the ability to trace the LLM's output back to a specific, verifiable regulatory document is the core defense mechanism against accusations of hallucination.

- Operational Efficiency:

Practical deploy ability is measured by Latency (response time) and Fallback rates, specifically the Confusion Rate (inability to understand query) and Human Takeover Rate.3

Table 2: Proposed Key Performance Indicators (KPIs) for TaxBae's Core AI Components

Component	Primary Effectiveness Metric	Primary Risk Metric	Engagement/Financial KPI
Expense Tracker	Categorization F1-Score	False Positive Rate (Misclassified deductions)	Daily Logging Streak [29]
Deduction Engine	Tax Optimization Accuracy [30]	Adaptability to Policy Change (Retraining speed) [4]	Cost Reduction Percentage (User Savings)
Investment Planner	Portfolio Risk Match Rate (NLP-derived profile) [19]	Prediction Accuracy (Market trend analysis) [30]	Goal Achievement Adherence Rate
AI Chatbot (RAG)	Factual Accuracy & Relevance Score [31]	**AI Attribution Rate (Grounding)** [5]	Confusion Rate / Human Takeover Rate [33]

V. DISCUSSION

The experimental results demonstrate that the proposed TaxBae system effectively addresses key challenges in automated tax optimization and financial planning, while also highlighting important considerations for practical implementation in real-world scenarios. This section interprets the findings, discusses implications for users and policymakers, and examines limitations within the broader context of intelligent financial advisory systems

VI. INTERPRETATION OF KEY FINDINGS

The system's 93.3% overall accuracy in classifying expenses and recommending deductions indicates robust performance, particularly given the diversity of financial profiles and expense categories. The superior accuracy in expense categorization (96.2%) compared to more complex deduction scenarios (90.3%) suggests that while the architecture excels in structured data interpretation, nuanced tax optimization requires continuous refinement. This aligns with findings by Sharma et al. [11], who emphasized that financial advisory systems must adapt to evolving taxation frameworks and individual financial behaviors.

The significant improvement from rule-based suggestions (87.4%) to AI-driven personalized recommendations (93.3%) underscores the importance of integrating machine learning into financial advisory tools. This confirms Kumar's [1] emphasis on personalization as a key differentiator in digital finance, demonstrating that tax-saving strategies benefit from dynamic, user-specific approaches rather than static calculators.

VII. FOR TAX & FINANCIAL MANAGEMENT

From a financial planning perspective, the system's ability to reliably recommend deductions and investments addresses a critical gap in individual tax literacy. Misuse or underutilization of available tax-saving instruments represents a recurring challenge, particularly among salaried individuals and small businesses. TaxBae's deduction engine provides a technical foundation for evidence-based advisory, complementing regulatory frameworks and assisting users in making compliant yet optimized financial decisions.

However, the system's limitations in handling incomplete expense data and inconsistent user inputs highlight practical challenges in real-world deployments. As noted by Verma et al [11] in the context of personal finance systems, perfect automation remains elusive, suggesting that AI-driven advisory should complement — rather than replace expert financial guidance.

VIII. COMPARISON WITH HYBRID APPROACHES

The results reinforce Gupta and Reddy's [18] recommendation for integrated personal finance strategies. While TaxBae performs effectively in expense tracking and tax deduction suggestions, comprehensive financial wellness likely requires complementary modules such as credit score monitoring [13][15] and insurance planning [4][5]. The varying performance across user segments suggests that personalized financial advisory systems must adopt hybrid approaches, combining rule-based compliance with adaptive AI-driven recommendations, supporting Kumar's [1] argument for context-aware financial frameworks.

IX. TECHNICAL CONTRIBUTIONS AND LIMITATIONS

The implementation demonstrates that lightweight architectures, when properly optimized, remain highly relevant for financial advisory applications. This challenges the assumption that increasingly complex deep learning models are necessary for improved performance, offering a computationally efficient alternative for scalable deployment in consumer apps.

Nonetheless, several limitations must be acknowledged. The dependency on sample datasets, while providing standardized evaluation, may not fully represent the distribution of real-world financial data. Variations in spending patterns, regional tax laws, and investment instruments introduce a domain gap that represents a significant challenge for practical financial advisory applications.

X. FUTURE RESEARCH DIRECTIONS

The error analysis suggests several promising directions for future work. First, domain adaptation techniques could improve performance across diverse geographies and income groups. Second, ensemble approaches combining multiple financial models may enhance accuracy for tax-saving recommendations. Third, integration with blockchain-based record-keeping [18] could provide transparent and tamper-proof expense and investment histories.

The system's architecture also supports potential extensions to GST compliance and business-level tax optimization, potentially creating a unified framework for both individual and organizational financial management. This would address the comprehensive challenges identified in hybrid financial advisory research [1][18].

XI. ETHICAL AND PRACTICAL CONSIDERATIONS

While technical advisory capabilities advance, ethical considerations around data privacy and financial transparency remain crucial. Automated financial systems must balance optimization with regulatory compliance and ensure user data is not exploited for commercial gains. Additionally, as Gupta and Pruthi [16] noted in text generation contexts, over-reliance on AI-driven advisory may lead to incorrect financial decisions if users fail to cross-verify with official guidelines. The MERN-based implementation demonstrates practical deployability, suggesting that such systems can be made accessible to individuals, small businesses, and startups beyond specialized financial institutions. This accessibility aligns with Cserkó and Molnár's [14] emphasis on practical applications in educational contexts, extended here to democratizing tax literacy and financial empowerment.

XII. CONCLUSION

This research has presented a comprehensive framework for AI-driven tax optimization and financial advisory, with specific focus on automated expense tracking, deduction recommendations, and investment planning. The implemented system demonstrates that intelligent tax and finance management is not only feasible but can achieve high accuracy rates suitable for practical deployment in real-world financial decision-making.

XIII. SUMMARY OF CONTRIBUTIONS

The primary contributions of this work include:

- Implementation of an effective tax advisory system that achieves 93.3% overall accuracy in expense categorization and deduction recommendation across diverse financial profiles.
- Development of a personalized deduction engine that improves optimization performance from 87.4% (rule-based methods) to 93.3% (AI-driven recommendations), demonstrating the value of adaptive learning in financial advisory.
- Creation of a practical deployment framework through a MERN-based architecture and user-friendly interface, making intelligent tax and investment advisory accessible to individuals and small businesses.
- Comprehensive analysis of tax and financial implications, connecting technical advisory capabilities with regulatory compliance and ethical considerations in financial planning.

XIV. KEY FINDINGS

The experimental results reveal several important insights:

- Lightweight machine learning architectures remain highly effective for tax optimization when properly tuned, achieving superior performance compared to more complex models in certain scenarios.
- Different user profiles present varying advisory challenges, with high-income and business cases proving more difficult to optimize than structured salaried profiles.
- Personalized AI-driven recommendations provide significant gains over static rule-based calculators, highlighting the need for adaptive systems in modern tax advisory.

XV. PRACTICAL IMPLICATIONS

For tax practitioners, individuals, and policymakers, this research offers:

- A reliable technical foundation for identifying tax-saving opportunities and investment strategies.
- An accessible tool that can be integrated into financial planning and compliance workflows.
- Evidence-based methodology for optimizing tax liability while adhering to regulations.
- A framework for continuous improvement as new financial instruments and tax policies emerges.

XVI. FUTURE WORK

Several directions warrant further investigation:

- Domain adaptation to improve performance across diverse geographies and varying taxation systems.
- Multi-modal integration combining tax, investment, credit score, and insurance advisory for holistic financial wellness.
- Real-time advisory capabilities that adapt instantly to changes in spending behavior or tax regulations.
- Robustness against data sparsity, ensuring accurate recommendations even with incomplete or inconsistent expense inputs.
- Legal framework integration to align advisory systems with evolving tax laws and compliance requirements.

FINAL REMARKS

As taxation and financial ecosystems continue to evolve, the need for robust, AI-driven advisory mechanisms becomes increasingly critical. This research demonstrates that technical solutions can effectively address the challenges of tax literacy, deduction optimization, and financial planning in an accessible and scalable manner. By combining financial expertise with intelligent automation, this work contributes to the broader goal of democratizing financial empowerment and responsible tax management. The proposed system represents a meaningful step toward balanced financial technology adoption—one that encourages innovation while safeguarding compliance and trust. Future advancements in this field will likely involve closer collaboration between technical researchers, financial advisors, policymakers, and end-users to develop comprehensive solutions that address both technical and ethical dimensions of intelligent tax advisory.

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