Wealth - AI-Powered Finance Management Platform

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***Abstract*—Manual expense tracking is often inconsistent and labor-intensive, leading to poor financial management. There are automated solutions, but most of them use intrusive Notification Access permissions, which put users' privacy and security at risk. This paper introduces Welth, an AI-powered personal finance management platform aimed at automating expense tracking while emphasising data sovereignty. The system replaces invasive monitoring with secure Gmail API integration (via OAuth 2.0), which filters and extracts transaction details strictly from digital invoices to ensure data persistence without accessing private communications. Concurrently, an Intelligent OCR engine creates a unified data pipeline by converting unstructured physical receipts into structured digital records.**

The platform is architected using Next.js and Tailwind CSS for a responsive user interface, with Supabase and Prisma ORM handling backend data synchronisation. Furthermore, the Google Gemini API is leveraged to provide contextual categorisation and generate personalised financial insights. Visualisation through Recharts and automated budget alerts empowers users to maintain financial discipline. This approach offers a secure, automated alternative to traditional tracking methods, significantly reducing manual effort without sacrificing digital privacy.

***Index Terms*—Personal Finance, Automation, Gmail Parsing, OCR, React, Web Application, Receipt OCR, NLP, Rule-based Extraction, Gemini, Expense Tracking, Supabase.**

I. INTRODUCTION

The rise of digital payments has made spending money easier. However, it leads to whole new problems: financial data is now spread across many different places—SMS, emails, bank apps, and paper receipts. Users struggle to understand their true financial health because this data is not in one place.

A. *The Problem with Solutions*

People usually try to manage their expenses either by writing them down manually or by using automated apps. But both approaches have big drawbacks:

Manual Tracking Fails: Writing expenses by hand is boring and takes a lot of time. People often forget small payments, lose paper bills, or struggle to organise messy receipts in spreadsheets. This makes mistakes very common.

SMS Tracking is Unreliable: Many apps depend on SMS alerts to record transactions. This is unreliable because not all payments (like international transfers or email invoices) generate an SMS. If a user deletes a message, that expense record is gone forever.

Privacy Risks: To overcome SMS limits, some apps ask for "Notification Access." This is risky because it lets them read every notification on the phone, including private messages and OTPs, which breaks user trust.

Lack of Intelligence: Most apps only show simple charts, like pie graphs. They don't explain why someone is over- spending or how to fix it. They act like "black boxes," giving numbers but no meaningful advice

B. *Our Solution: Welth*

To solve these issues, this paper presents Welth, a privacy-focused finance platform. Instead of using risky permissions, Welth uses the Gmail API (with secure OAuth login) to automatically fetch transaction emails. For paper bills, we use an OCR system to convert images into text. Finally, we use the Google Gemini API (AI) to clean up these data and give the user smart, explained insights about their spending habits.

II. LITERATURE REVIEW

A. ***Walnut (Axio) — Comparison***

Walnut (Axio) is a market-leading expense tracker that automates financial logging by parsing SMS notifications [1], [2]. However, a comparative analysis highlights four critical areas where Welth offers a superior architecture:

- **Privacy and Security:** Walnut requires permissions to "Read SMS", which exposes private messages and OTPs to the application [3]. In contrast, Welth utilises the Gmail API with OAuth 2.0, operating on a *Least Privilege* model that accesses only transaction-specific emails, ensuring user data sovereignty.

- **Data Completeness:** Walnut is unable to track non-digital transactions (cash) or online purchases that do not trigger an SMS notification [4]. Welth resolves this by integrating an Intelligent OCR engine to digitise physical receipts, creating a truly unified financial record.
- **Analytical Intelligence:** While Walnut provides basic, rule-based categorisation, it lacks depth and adaptabil- ity [5]. Welth leverages Google Gemini (GenAI) to provide Explainable AI insights, offering users context-aware advice and identifying spending anomalies that static rule- sets miss.
- **Platform Independence:** Walnut's data is tied to the device's local SMS history; deleting messages may lead to permanent loss of expense records [6]. Welth employs a cloud-native architecture (Supabase), ensuring persistent data storage and enabling a comprehensive Web Dash- board for advanced analytics not possible on mobile-only systems.

B. CRED Comparison

CRED is a specialised fintech platform focused on rewarding credit card users. Although effective for its niche, a technical analysis reveals three major limitations that Welth addresses for holistic financial management [7], [8].

Scope and Utility

CRED functions primarily as a credit card bill payment platform, offering rewards to encourage spending. It structurally ignores UPI, debit card, and cash transactions, which constitute the majority of daily expenses for most users [9]. Welth, conversely, offers full-spectrum tracking, aggregating data across all payment modes—Card, UPI, and Cash—to provide a complete picture of financial health rather than just credit liability.

Data Ingestion and Offline Gaps

CRED relies on limited email scanning and SMS reading to track card statements. It lacks an ingestion pipeline for physical bills. Welth overcomes this by integrating an Intelligent OCR engine, allowing users to digitise paper receipts instantly, ensuring that offline spending is not excluded from the financial ledger [10].

User Intent and Ethics

Research indicates that CRED employs "Dark Patterns" and gamification (coins, jackpots) to encourage higher credit card usage [11]. In contrast, Welth is architected as a pure utility tool. It eliminates marketing-driven psychology and focuses on Financial Clarity, using AI not to sell rewards, but to detect overspending and promote saving behaviour.

C. MoneyView Comparison

MoneyView is a widely known financial platform in India that combines expense tracking with credit products [12]. However, its primary business model is selling personal loans, creating a conflict of interest with the user's goal of financial well-being [13]. Welth addresses these limitations through a privacy-first, utility-focused architecture.

Monetisation vs. Financial Health

MoneyView's Conflict: The platform generates its core revenue by cross-selling personal loans [13]. Even the user in-terface is designed to promote credit products rather than purely analysing expenses, creating an environment that distracts users from the primary goal of saving.

Welth's Utility: Wealth operates as a neutral financial tool. It is architected without a lending module, ensuring that AI insights are biased strictly towards saving and investing, rather than encouraging debt accumulation.

Data Ingestion and Privacy

MoneyView's Limitation: Like Walnut, MoneyView relies on reading SMS logs to track spending [14]. This requires permissions that expose a user's message history to developers. Furthermore, it fails to parse email-based invoices (e.g., Apple receipts, flight tickets) or track physical cash spending.

Welth's Solution: Welth unifies data through a *Three-Source Pipeline*: Gmail API for digital invoices, Intelligent OCR for paper receipts, and manual entry for petty cash. This ensures 100% data coverage without requiring dangerous SMS permissions.

Categorization Accuracy

MoneyView's Limitation: The application uses static key-word matching (e.g., if "Shell" is found, categorise as "Fuel") [15]. This approach often fails with ambiguous merchant names or new UPI IDs, resulting in frequent incorrect classification.

Welth's Innovation: By utilising Google Gemini's Semantic Reasoning [16], Welth understands the context of a transaction. It can correctly identify that a payment to "Amazon" could be for "Groceries" (Pantry) or "Electronics," based on email invoice details, delivering superior categorisation accuracy.

D. GoodBudget Comparison

GoodBudget is a popular budgeting application based on the traditional "Envelope Method." Although it excels in manual budget planning, it shows several critical deficiencies in handling the high-volume, digital-first transaction ecosystem of modern India [20]. Welth fills these gaps through end-to-end automation.

Manual Entry vs. Automated Ingestion

GoodBudget's Limitation: The platform requires 100% manual inputs. It does not integrate with SMS, Email, or Bank APIs to fetch transactions. This high-friction model forces users to manually log every UPI payment, card swipe, and cash expense. Research suggests such manual systems suffer from high user attrition due to cognitive load and time commitment requirements [18].

Welth's Solution: Welth implements a zero-touch ingestion pipeline. By utilising the Gmail API to auto-fetch digital invoices and an OCR engine to scan physical receipts, it eliminates manual data entry, ensuring real-time ledger updates without user intervention.

Scope of Financial Tracking

GoodBudget's Limitation: Due to its manual nature, GoodBudget is often used only for budgeting specific categories (e.g., "Groceries"), rather than tracking complete wealth. It lacks the infrastructure to monitor cross-platform spending behaviours across UPI apps, net banking, and credit cards simultaneously.

Welth's Advantage: Welth provides a unified dashboard that collects data from all sources—email invoices (online shopping), OCR scans (offline retail), and manual logs (petty cash). This offers a complete view of financial health that manual envelope systems cannot replicate.

Static Rules vs. AI Intelligence

GoodBudget's Limitation: The application relies on the user to manually assign categories and limits. It lacks predictive capabilities or automated insights; it cannot warn a user before they overspend based on historical trends.

Welth's Innovation: Welth uses Machine Learning (ML) and Generative AI (Gemini) to offer predictive budgeting. It not only categorises expenses automatically but also forecasts future spending liabilities and provides real-time, context-aware alerts to prevent budget breaches [19].

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III. PROBLEM STATEMENT

The digitalisation of society is increasing rapidly, and most of society has adopted the Unified Payments Interface (UPI) and digital wallets, due to which financial transactions have increased quickly.

Existing solutions are not able to solve these problems due to structural flaws:

***Security and Privacy Risks**:* Famous automated platforms rely on "Notification Access" to parse SMS. This violates the principle of privacy by exposing One-Time Passwords (OTPs) and private communication to third-party apps.

***Data Incompleteness**:* SMS-based systems fail to capture those transactions that do not send SMS notifications, for example: International payments, subscription renewals, and email invoices. On the other hand, apps that require manual entry often lose users because it is too much work to record every expense.

***Lack of Explainability**:* Most personal finance apps only show basic charts to describe spending, But they do not explain the reasons behind the spending, and cannot provide advice that considers the user's specific situation.

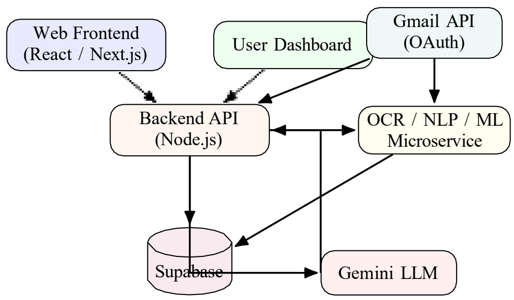
IV. OBJECTIVE

The objective of this research is to develop an automated and secure finance management system that consolidates all separate financial records into one unified platform by using email invoices, OCR-scanned receipts, and manual cash entries. To achieve this, the system integrates hybrid OCR techniques, NLP rules, ML models, and Gmail-API–based data ingestion.

1) Developing a system that reads receipts.
2) Rule-based extraction to find the store name, date, total amount, tax, and each item on the receipt.
3) Build a small ML tool to improve categorisation, spot unusual transactions, understand context, and let the user have control.
4) Build a dashboard to visualise expenses, trends, categories, and monthly patterns, and allow editing, deletion, or fixing of expense records.
5) Safe email parsing with minimum permission needed to fetch invoice emails without disrupting privacy.
6) Develop a single system that can combine data from three sources—receipts scanned, invoices fetched, and manual expense entry.
7) Smart AI suggestions about budgets and how to spend money better.

V. SYSTEM ARCHITECTURE

System Architecture Diagram



The system architecture of Welth collects expense records from email receipts and cash notes, keeps them private, organises them neatly, and presents simple insights to help users manage their money better. It follows a multi-layered architecture, including Ingestion Services, Preprocessing & OCR Modules, NLP & ML Layers, Cloud Database, API Backend, and an LLM-Powered Insight Engine. Figure ¡¡Architecture Diagram Placeholder¿¿ illustrates the high-level flow of data from ingestion to dashboard visualisation.

- **Ingestion Layer:** The ingestion layer collects financial data through three ways: user-uploaded receipt pictures on the website, Gmail invoices through the Gmail API (OAuth) without accessing the full inbox, and manual cash entry.

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- **OCR Microservice:** The OCR microservice performs image cleaning by removing extra marks, adjusting brightness and contrast, and fixing tilted or skewed images. A hybrid OCR strategy is used, where tools like Tesseract and cloud OCR services read the receipt, and the system compares their results.
- **NLP and Rule-Based Extraction:** The NLP and rule-based extraction layer transforms raw text into structured fields. This includes regex parsing for dates and totals, keyword extraction, and fuzzy search for merchant name matching. Data is formatted so that every transaction follows the same structure, ensuring clean and consistent results.
- **LLM Layer:** Only structured, non-sensitive fields are sent to Gemini. The LLM converts this data into easy- to-read insights and provides AI-driven suggestions for better financial management.
- **Database Layer:** The database layer, implemented using Supabase/PostgreSQL, stores transactions, merchant in-formation, receipt records, and user profiles. All data is encrypted with strict user isolation, enabling fast dashboard retrieval and report generation.
- **Backend Layer:** The backend layer provides secure REST endpoints for receipt upload, email-sync triggers, OCR/NLP processing, analytics queries, and insight generation. Heavy processes are queued to worker servers to keep the user interface fast and responsive.
- **Frontend Layer:** The frontend layer provides a responsive interface to upload receipts, track expenses, edit entries, and view monthly spending trends, category distributions, and transaction timelines. The screens include login, upload, transaction list, transaction edit, and dashboard views.

VI. METHODOLOGY

The methodology describes how Welth handles financial data. It collects information from emails, scanned receipts, and manual cash entries, then cleans and organises it so it's easy to work with. The system follows a multi-stage process: first, it brings in Gmail data, then it preprocesses and reads receipts using a mix of OCR tools, extracts key details with language rules (NLP), improves accuracy with machine learning, and finally uses an advanced AI engine (LLM) to turn the results into clear insights, budget tips, and spending explanations.

A. Email Ingestion (Gmail API)

Welth connects to Gmail with limited read-only access, fetches only transaction-related emails like UPI, card state- ments, or invoices, and then converts the email content into structured details such as merchant, amount, date, and category.

B. Receipt Preprocessing

Uploaded receipt images are first cleaned by converting to grayscale, removing marks, enhancing text, and straightening tilted images so OCR can read them more accurately.

Let the input image be I. Preprocessing is modelled as:

$$I_{\text{clean}} = T(S(N(G(I))))$$

Where: G = grayscale, N = noise reduction, S = skew correction, T = thresholding.

C. Hybrid OCR Extraction

Both Tesseract and a Cloud OCR engine process the cleaned image:

$$O_1 = \text{Tesseract}(I_{\text{clean}}), \qquad O_2 = \text{CloudOCR}(I_{\text{clean}})$$

A scoring function selects the more accurate output:

$$Score = \alpha \cdot Conf + \beta \cdot FieldCompleteness$$

Where $\alpha = 0.6$ and $\beta = 0.4$. Final OCR output:

$$O_{\text{final}} = \begin{cases} O_1, & \text{if } Score_1 > Score_2 \\ O_2, & \text{if } Score_2 > Score_1 \end{cases}$$

D. NLP and Rule-Based Field Extraction

OCR and email text are processed using simple rules and patterns. The system detects dates, extracts the total amount, identifies merchants even with spelling variations (fuzzy matching), and parses GST or tax details, turning raw text into clean, structured financial information. Fuzzy matching uses the Levenshtein similarity:

E. ML-Based Classification and Anomaly Detection

A lightweight ML model refines categories using merchant keywords, invoice context, and amount patterns. Anomalies are detected using z-scores:

$$z = \frac{x - \mu}{\sigma}$$

Transactions with $|z| > 2.5$ them are flagged as unusual.

F. Record Normalization

All extracted fields are converted into a unified structured format:

{merchant, date, amount, tax, type, category}

This ensures consistency across receipts, emails, and manual entries.

G. LLM-Powered Insight Generation (Gemini)

Welth sends only safe, structured details like totals, dates, and merchant names to Gemini. Using this data, Gemini produces clear spending summaries, gives budget tips, explains spending behaviour, and alerts users about overspending.

H. Storage and Dashboard Rendering

Wealth stores all cleaned records in a secure Supabase/Post-greSQL database with encryption and strict row-level security, so each user only sees their own data. The dashboard then pulls summarised insights using fast SQL queries that are sped up with indexing for quick analytics.

VII. IMPLEMENTATION

Welth is built in a modular way, with each part of the system handling its own job separately—like the frontend for users, backend for requests, OCR/NLP for text processing, Gmail ingestion for emails, the database for storage, and AI engines for insights. All of this runs as a cloud-scalable web platform, designed to be reliable, secure, and able to grow easily as more users join.

The web frontend of Welth is built with Next.js and React, offering pages for login, receipt uploads, transaction lists, editing, and dashboards. It connects to the backend through HTTPS and uses Recharts to display spending trends, categories, and detailed insights. Before sending receipts for processing, the frontend makes sure they meet requirements by checking their size and format.

The backend API, built with Node.js and Express, handles key functions like user login, Gmail syncing, sending receipt images to the OCR service, and answering analytics requests. It keeps data secure with strict validation, JWT authentication, and role-based access control. To stay fast, heavy jobs such as OCR and machine learning are sent to background workers instead of running directly in the main system.

The OCR/NLP/ML microservice, built with Python FastAPI, handles the heavy processing work. Receipt images are first cleaned (grayscale, noise removal, thresholding, skew correction) and then processed by both Tesseract and a Cloud OCR engine, with the better result chosen automatically. NLP rules extract dates, amounts, merchants, and other details, while fuzzy matching improves accuracy. Finally, lightweight machine learning models refine expense categories and flag unusual transactions.

The Gmail ingestion pipeline connects using OAuth 2.0 with limited permissions, it fetches transaction-related information related to emails only, and converts them into structured details like merchant, date, amount, and descriptors. Then these records are sent to the backend and stored in the same format as receipt data for consistency.

All structured records are saved in a **Supabase/PostgreSQL database** with tables for receipts, Gmail invoices, merchants, categories, and user profiles. It ensures Security through row-level access controls and sensitive data encryption, while indexes on amount, date, and merchant make analytical queries faster.

The LLM layer, built on Google Gemini, is restricted to secure structured data. It creates clear insights like monthly summaries, budget tips, and explanations of unusual spending. All prompts are cleaned before sending, and responses are cached to make the dashboard faster.

Welth uses a containerised setup where the frontend runs on Vercel, the backend and microservices run on Railway or Docker servers, and the database is hosted on Supabase. GitHub Actions automatically run tests and manage versioned deployments. Logging, monitoring, and manual fallback reviews for OCR errors keep the system stable and reliable.

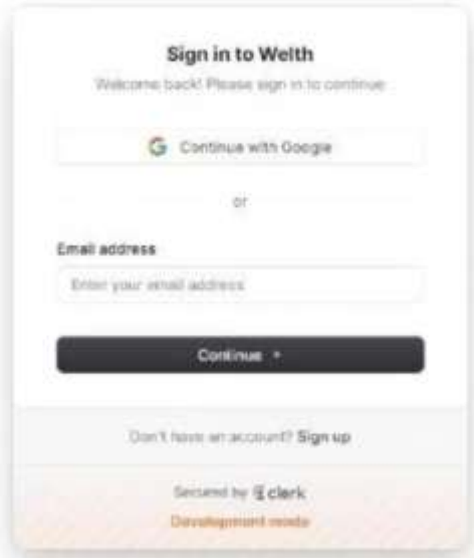

Fig. 1: Welth Login Page Interface

Fig. 2: Welth Landing Page

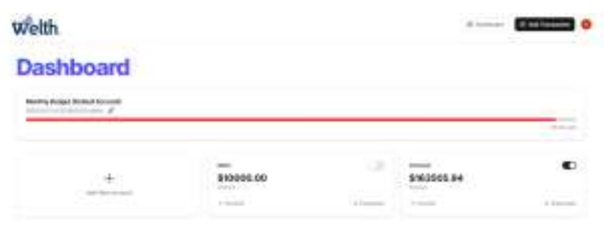

Fig. 3: Welth Dashboard

Fig. 4: It shows transactions, the expense graph, and transaction deletion

Fig. 5: Gmail alert

Fig. 6: Manual entry

VIII. Experiments and Results

A. Experiments and Results

We tested the system using 600 receipts — 412 real ones and 188 made-up examples — plus some extra computer-generated email invoices. The tests looked at four main things: how well the OCR read text, how accurately the NLP pulled out key details, how fast the whole pipeline ran, and how good the machine learning was at spotting unusual cases. To make the results easy to check, we share numbers for OCR accuracy at both character and word level, the field extraction accuracy (FEA) for important details, the average time taken at each step, and the F1 scores for the ML classifier.

TABLE I: OCR performance (600 receipts).

OCR Engine	CLA (%)	WLA (%)	FEA (%)
Tesseract (LSTM)	87.6	82.4	79.1
Google Vision API	94.3	91.7	88.9
Hybrid selection (ours)	**95.1**	**92.8**	**90.2**

1) OCR Performance: Notes: CLA = Character-Level Accuracy; WLA = Word-Level Accuracy; FEA = Field Extraction Accuracy (merchant, date, total, taxes). Hybrid selection uses a confidence score combining average OCR confidence and field completeness (=0.6, =0.4).

TABLE II: NLP extraction accuracy (field-level).

Field	Extraction Accuracy (%)
Merchant Name	93.4
Date	95.2
Total Amount	97.1
Tax Fields	89.6
Itemized Entries	84.3

2) NLP Field Extraction: Notes: Accuracy is computed against manually annotated ground truth. Merchant evaluation uses fuzzy-match acceptance threshold (sim 0.75).

TABLE III: Average pipeline latency (ms).

Pipeline Stage	Avg. Time (ms)
Image Preprocessing	122
OCR Extraction	410
NLP Parsing	148
Database Commit	67
Dashboard Rendering	133
End-to-End (median)	**880 ms**

3) Latency: Notes: Times measured on a moderate cloud instance (2 vCPU, 8 GB RAM). Heavy jobs are queued; end-to-end measures include queue wait times for median-case runs.

4) ML Classification and Anomaly Detection: We tested the system's ability to refine categories and spot unusual transactions using a separate 20% portion of the data (made up of both synthetic and corrected real examples). For this test, we report the classification F1 scores as well as the precision and recall values for anomaly detection.

TABLE IV: ML performance (category refinement & anomaly detection).

Task	Precision (%)	Recall (%)	F
Category-refinement (8 classes)	91.2	90.5	
Unusual-transaction detection (z-score + ML)	88.1	85.3	

Notes: Category-refinement uses a lightweight tree/ensemble model trained on labelled examples augmented by merchant and invoice text features. Anomaly detection combines z-score thresholding (—z—¿2.5) with a small supervised model for improved precision.

5) Summary: Overall, the mix of OCR and rule-based NLP works very well, reaching about **90% accuracy** in pulling out key fields. The system also runs quickly, with a typical response time of around **0.88 seconds**. On top of that, the lightweight machine learning parts help refine categories and catch unusual transactions, while still keeping the results clear and easy to understand.

IX. Future Scope

In the future, Welth can grow into a full Android app that securely reads SMS alerts for UPI and bank transactions, expanding coverage beyond emails. It could add multilingual OCR, stronger machine-learning for instant categorisation, and advanced integrations like GST invoice checks and merchant APIs. At a larger scale, Welth could become a modular financial intelligence engine for fintechs, retailers, or accounting platforms, automating categorisation, keeping privacy and transparency intact.

X. Discussion

The results show that Welth can reliably handle financial data by using Gmail-based data collection, a mix of OCR, rule- based NLP, and simple machine learning refinement. Compared to SMS-based trackers, the system works better in terms of data coverage, privacy, and clarity of results. According to results, Gmail ingestion captures a much wider range of digital transactions than SMS alone, while the OCR process maintains high accuracy even with messy or low-quality receipts. The machine learning parts help avoid classification mistakes and spot unusual transactions that users often miss when checking manually.

Key Observation: Welth's design decisions directly shape its strengths:

1) **Gmail OAuth** – avoids the privacy risks that come with SMS permissions.
2) **Hybrid OCR** – reduces the chance of losing information when scanning physical receipts.
3) **Rule-based NLP** – makes the system's processing clear and transparent.
4) **LLM-powered insights** – give explanation-based financial guidance that regular expense apps don't provide.

However, the study also points out some limits. The OCR tool does not work well on very poor-quality receipts, Gmail data collection only works if users give permission and have internet access, and the lightweight machine learning models sometimes need manual fixes when merchant names are unclear. Even with these challenges, the results show that **Welth** offers a financial record that is more ethical, private, and complete than traditional expense trackers, proving that the system is practical and useful for everyday users.

XI. Conclusion

Welth is an AI-powered finance app that brings together email invoices, scanned receipts, and manual entries into one secure system. It uses Gmail login, smart OCR (for reading text from images), rule-based NLP, and lightweight machine learning to accurately extract and organize financial data while keeping privacy safe.

Performance highlights:

- 95% accuracy in reading characters
- 90% accuracy in capturing key details
- Less than a second to process data

With the help of Gemini LLM, Welth turns raw financial records into clear insights so users can better understand and manage their spending. Even though it faces challenges with poor-quality receipts or unclear merchant names, it still offers more reliable and transparent tracking than SMS-based apps.

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