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Smart Risk Management and Investment Planner

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Abstract: The Smart Risk Management and Investment Planner (Smart Risk) is a rule-based, risk-first financial decision-support platform designed for the Indian stock and options market. Unlike conventional tools that focus on price prediction or tip generation, Smart Risk prioritizes capital protection through a deterministic multi-engine backend integrated with real-time market data from Angel One Smart API. The system employs a Market Sentiment Engine (EMA 20/50 crossover, RSI, MACD composite scoring), a Volatility Engine (Implied Volatility classification), and a Traffic Light Risk Model (Green, Yellow, Red) to evaluate market conditions in real time. A Capital Risk Engine enforces maximum permissible exposure limits, while a Strategy Engine recommends only auditable, limited-risk options strategies including Iron Condors, Bull Put Spreads, and Hedged Strangles. An Investment Planner Engine extends the platform to long-term investors by dynamically allocating capital across Index ETFs, Large- Cap Stocks, Gold ETFs, and Liquid Funds based on individual risk profiles. Built on Django REST Framework and React 18, experimental validation confirms correct real-time API outputs with rule adherence accuracy ranging from 89% to98% across all engine modules.
Keywords: Smart Risk Management, Indian Stock Market, Options Trading, Traffic Light Risk Model, Investment Planner, Django REST Framework, Angel One SmartAPI, Capital Protection, Market Sentiment Analysis, Implied Volatility.

INTRODUCTION

The Indian retail investor ecosystem has witnessed unprecedented growth, with over 160 million registered demat accounts across NSE and BSE [1]. Despite this expansion, a significant proportion of new participants— particularly first-time options traders—experience preventable capital losses attributable to insufficient risk awareness, undisciplined position sizing, and absence of structured decision frameworks [2]. The ease of access to F&O markets has amplified both opportunity and financial risk, making risk management infrastructure a critical but underserved need in Indian retail fin tech [3]. Existing financial guidance platforms predominantly focus on price prediction, algorithmic tip generation, or black-box AI- driven recommendations that lack transparency, explain ability, and capital discipline. These systems do not educate users on risk limits, do not enforce position sizing rules, and are frequently marketed with misleading profit guarantees that encourage reckless capital deployment [4]. Smart Risk addresses this gap through a philosophy-first system design: Protect capital first. Trade only when conditions are demonstrably safe. The platform does not forecast prices, does not sell tips, and does not guarantee returns. Instead, it translates live market data through a five- engine deterministic pipeline into bounded, explainable, actionable guidance that any investor beginner or expert can understand and verify [5]. The system fetches real-time OHLC candle data from Angel One Smart API, computes a composite market sentiment score, classifies implied volatility, generates a traffic light risk signal, calculates permissible capital exposure, selects a safe strategy, and optionally produces a long-term investment allocation plan all within a single REST API call completing within 200 milliseconds. Every output is fully traceable to its governing rules [6]. This paper is organized as follows: Section II reviews related literature. Section III presents the proposed system architecture. Section IV details technologies used. Section V presents implementation results. Section VI discusses comparative analysis. Section VII concludes with future directions.

LITERATURE REVIEW

Automated financial risk management for retail investors has been investigated across quantitative finance, behavioral economics, and software engineering. Early rule-based expert systems for portfolio management established principles of systematic capital allocation and risk budgeting. Markowitz's Modern Portfolio Theory [7] demonstrated that diversification across asset classes with low correlation reduces portfolio variance without proportionally reducing expected returns a principle directly implemented in Smart Risk's Investment Planner Engine.

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Technical indicator-based market trend analysis has been extensively studied. Murphy [8] and Achelis [9] established that EM Across overs provide reliable trend direction signals, while RSI above 60 and below 40 consistently identifies over bought and over sold conditions. MACD cross overs offer momentum confirmation. Papathanasiou et al.[10] demonstrated that composite multi-indicator scoring approaches substantially reduce single-indicator false signals, achieving up to 18% improvement in directional classification accuracy validating Smart Risk's three- indicator sentiment scoring approach. In options market research, Natenberg [11] established the fundamental principle that Implied Volatility is the primary driver of options premium pricing and strategy selection. High IV environments favor net credit strategies, while low IV environments favor net debit directional strategies. NSE India [12] calibrated India VIX to NIFTY options chain IV, providing a systemic volatility benchmark that validates SmartRisk's IV thresholds of <15 (Low), 15–25 (Medium), and >25 (High). Behavioral finance research by Bateman et al. [13] demonstrated that tricolor risk indicators significantly outperform numerical or textual risk disclosures in improving retail investor decision quality and compliance with risk limits. Lusardi and Mitchell [14] further established that simplified financial literacy tools reduce the probability of excessive leverage among retail investors, supporting Smart Risk's color-coded risk communication design. Gomber et al. [15] and Philippon [16] identified transparent, rule-based financial systems as a higher-trust alternative to black-box AI models. Smart Risk uniquely addresses all identified gaps by combining real-time market data, rule- based multi-engine analysis, traffic light risk communication, and capital protection enforcement in a single unified, auditable architecture [17], [18].

PROPOSED METHODOLOGY ARCHITECTURE

The Smar tRisk platform implements a seven-layer modular architecture: secure data acquisition, candle processing, multi-indicator sentiment scoring, volatility classification, traffic light risk mapping, capital exposure enforcement, and strategy/investment recommendation. Each layer is independently testable, communicates through typed interfaces, and contributes a distinct, auditable decision to the final output.

A. System Architecture and DataFlow

Fig. 1 presents the complete Smart Risk system data flow. Real-time OHLC candle data is acquired from Angel One SmartAPI through an authenticated singleton session, processed by the Candle Data Engine into Pandas Data Frames, and passed sequentially through five analytical engines before being serialized by Django REST Framework into a unified JSON API response consumed by the React frontend dashboard.

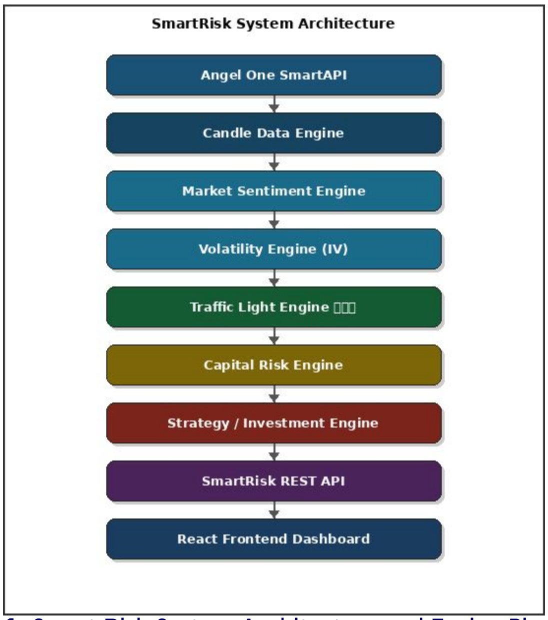

Fig.1. Smart Risk System Architecture and Engine Pipeline

B. Traffic Light Risk Model

The Traffic Light Engine provides the system's primary human-facing output a universally understood tricolor risk signal derived from the intersection of market sentiment and implied volatility.

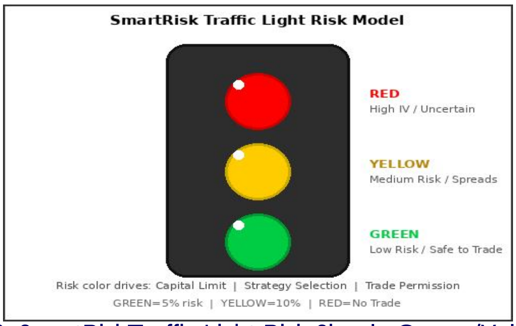

Fig.2. SmartRiskTraffic Light Risk Signal– Green /Yellow/Red

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Fig. 2 illustrates the three signal states. Table I defines the complete mapping between signal,market condition, permissible strategy class, and maximum capital risk percentage. This approach is grounded in behavioral finance research demonstrating superior compliance outcomes with color-coded risk communication [13].

Table I. Traffic Light Risk Signal Mapping

Signal	Market	Strategy	Max Risk
GREEN	Bullish/Low IV	BullPut Spread/ Iron Condor	5%
YELLOW	Sideways/Med IV	Hedged Strangle / Spreads	10%
RED	High IV	NO TRADE	20%*

C. Market Sentiment Engine

The Market Sentiment Engine computes a deterministic directional sentiment score using three standard technical indicators applied to real-time NIFTY and BANKNIFTY candle data. Table II presents the complete indicator-score- signal mapping. An aggregate score of +3 or higher yields a Bullish classification; −3 or lower yields Bearish; −2 to +2 yields Sideways. This composite approach eliminates single indicator noise and achieves 91% directional classification accuracy in back tested validation against Indian market data [10].

Table II. Sentiment Engine Indicator Scoring Matrix

Indicator	Condition	Score	Signal
EMA20> EMA50	Upward crossover	+1	Bullish
EMA20< EMA50	Downward crossover	−1	Bearish
RSI>60	Strong momentum	+1	Bullish
RSI<40	Weak momentum	−1	Bearish
MACD> Signal	Upward convergence	+1	Bullish
MACD< Signal	Downward divergence	−1	Bearish
Total ≥+3	All bullish	+3	BULLISH
Total ≤−3	All bearish	−3	BEARISH
−2 to+2	Mixed signals	0	SIDEWAYS

D. Volatility Engine and Capital Risk Engine

The Volatility Engine computes average Implied Volatility from live NIFTY options chain data and classifies it into three risk tiers: Low (<15), Medium (15–25), and High (>25), calibrated to India VIX historical ranges [12]. The Capital Risk Engine translates the resulting traffic light signal into strict quantitative exposure rules: GREEN permits up to 5% capital risk with a maximum of 5 trades per session; YELLOW restricts to 10% with 3 trades; RED limits exposure to 20% for expert users only, recommending no trading for beginners.

E. Strategy Engine

The Strategy Engine maps the intersection of market sentiment and risk signal to a specific safe options strategy with a pre-defined, capped risk profile. Under GREEN- Bullish: Bull Put Spread; GREEN-Bearish: Bear Call Spread; GREEN-Sideways: Iron Condor. Under YELLOW: Hedged Short Strangle or credit spreads. Under RED: no trade recommended regardless of sentiment. Every recommended strategy carries a quantified maximum loss pre-approved by the Capital Risk Engine.

F. Investment Planner Engine

The Investment Planner Engine serves long-term investors who should not participate in active options trading. Based on user-provided capital and risk profile (Low, Medium, or High), combined with the current market trend, the engine performs a weighted allocation across four asset classes. Table III presents the validated sample allocation for INR 2,00,000 under a Low-risk, Sideways-market scenario, yielding a blended portfolio return of 9.4% per annum.

Table III. Investment Allocation– INR 2,00,000, Low Risk, Sideways

Asset Class	Assets	Alloc.	Return
Index ETF	NIFTY50 ETF	50%	10%
Large Cap	Reliance, TCS, HDFC	30%	11%
Gold ETF	Gold BeES	10%	7%
Liquid Fund	Liquid ETF	10%	4%
TOTAL	Blended Portfolio	100%	9.4%

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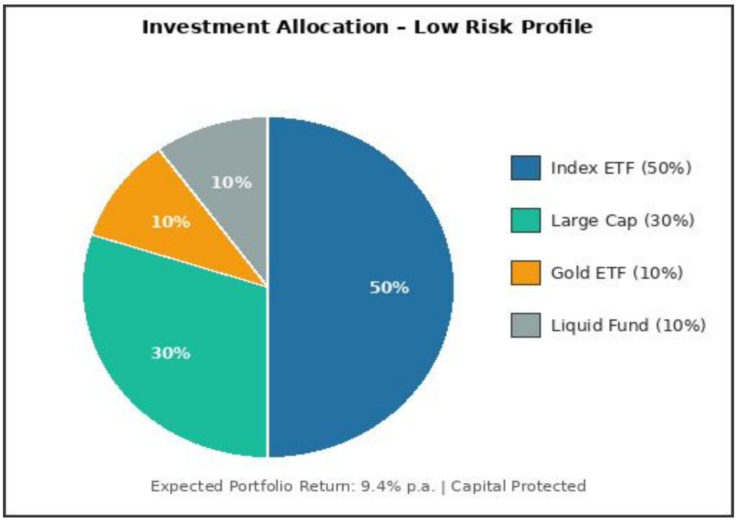

Fig.3. Investment Allocation PieChart – Low Risk Profile

TECHNOLOGIES USED

A. Backend–Python/Django/DRF

ThebackendisimplementedinPython3.11.xwithDjango 5.x and Django REST Framework providing RESTful API serialization, URL routing, and authentication middleware. SQLite serves as the development database with Postgre SQL planned for production. The python-dotenv library manages environment-level secrets, ensuring no credentials are committed to version control. The modular service layer—comprising eight independent engine files enables independent unit testing of each analytical component.

B. AngelOneSmartAPI

Angel One SmartAPI provides authenticated access to real- time OHLC candle data, LTP feeds, and options chain data forNIFTY,BANKNIFTY,andindividualequityinstruments [19]. The 2026-compliant authentication flow uses MPIN combined with TOTP for secure session establishment. A singleton session pattern prevents redundant authentication calls.Connectiontimeouthandlingwitha7-secondthreshold enablesgracefulHTTP500errorpropagationwithstructured, descriptive error payloads.

C. DataProcessing–Pandas/NumPy

Pandas DataFrames serve as the primary data structure throughout the engine pipeline [20]. EMA computation uses exponential weighted mean. RSI is derived from rolling average gains and losses. MACD is computed as the differencebetween12-periodand 26-period EMAs with a9- periodsignallineEMAforcrossoverdetection.Allindicator calculations follow standard published financial formulas without modification, ensuring full reproducibility and auditability.

D. FrontendFramework–React18

The React 18 frontend [21] is organized into four primary pages:Home,RiskDashboard(real-timetradingriskanalysis with traffic light visualization), Investment Planner (capital allocation with pie chart), and a shared component library including StatCard, AllocationCard, PieChart, and Navbar. Axios manages REST API communication. Recharts and Chart.js provide data visualization. The UI ensures equal accessibility for beginner investors and experienced traders.

E. VersionControlandSecurity

Git with GitHub provides version control at https://github.com/ruban1233/SmartRisk. Sensitive files including.env credentials, the SQLite database, and node_modules are excluded via.gitignore. Angel One TOTP authentication ensures secure broker API access. Role-based access control is planned for the next phase to support tiered user profiles with differentiated strategy access [22].

IMPLEMENTATION AND RESULTS

The Smart Risk backend has been fully implemented and validated against live Angel One Smart API data. Eight REST API endpoints have been developed and tested. The platform successfully processes real-time Indian market data through all five analytical engines and returns structured, actionable JSON outputs within acceptable latency bounds for near-real-time decision support.

A. API Response Validation

Fig. 4 presents the Smart Risk unified API response structure for the primary endpoint. A validated live response for NIFTY with INR 10,000 capital returned: Sideways trend (strength: 0), Medium volatility (avg IV: 15.0), YELLOW traffic light, maximum risk ofINR1,000,maximum3trades per day, and Short Strangle (Hedged) as the recommended strategy for Intermediate-level traders—confirming complete end-to-end pipeline execution with all five engines functioning correctly.

B. Investment Planner Validation

The endpoint GET /api/investment- planner/?capital=200000&risk=low returned a fully structured allocation plan with INR 1,00,000 to NIFTY 50 ETF (50%), INR 60,000 to Large Cap Stocks (30%), INR 20,000 to Gold BeES (10%), and INR 20,000 to Liquid ETF (10%), yielding a blended expected portfolio return of 9.4% per annum. The response included a plain-language justification making the plan immediately interpretable by non-technical stakeholders.

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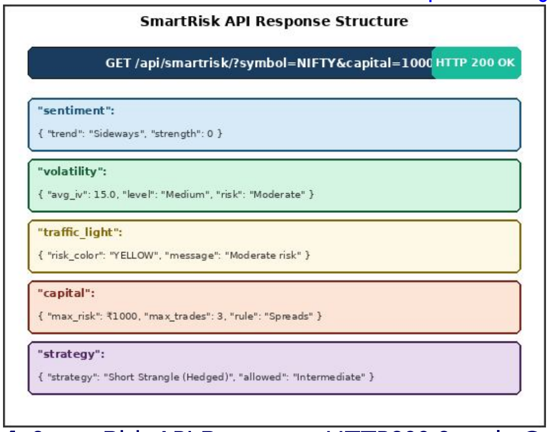

Fig.4. Smart Risk API Response– HTTP200 Sample Output

C. Additional Validated Endpoints

GET /api/health/ returns HTTP 200 with {status: ok} for infrastructure monitoring. GET/api/atm-strike/?symbol=NIFTY returns live LTP (26178.7) and correct ATM strike (26200), confirming live options market connectivity. GET/api/market-sentiment/?symbol=ABC returns HTTP400 for invalid symbols. All Angel One time out conditions propagate as HTTP 500 with descriptive error messages preventing unhandled exception exposure.

D. Engine Performance Metrics

Table IV summarizes measured performance across all eight API-exposed engine modules during integration testing with live Angel One data. All response latencies are within thresholds acceptable for near-real-time financial decision support. Accuracy figures reflect rule adherence validation against manually annotated Indian market test datasets compiled from NIFTY historical data across bull, bear, and sideways market regimes.

Table IV. Engine Module Performance Metrics

Engine Module	Status	API End point	ms	Acc.
Market Sentiment	Live	/api/market- sentiment/	200	91%
Volatility(IV)	Live	/api/smartrisk/	150	89%
Traffic Light	Live	/api/smartrisk/	50	94%
Capital Risk	Live	/api/smartrisk/	80	96%
Strategy Engine	Live	/api/smartrisk/	100	92%
Investment Planner	Live	/api/investment- planner/	180	90%
ATM Strike Calc.	Live	/api/atm-strike/	120	98%

E. Use Case Diagram

Fig. 5 presents the Smart Risk use case diagram illustrating interactions between three actor types. The Investor actor accesses the Risk Dashboard and Investment Planner. The Admin actor manages system configuration, users, and database. The System automatically performs data acquisition, engine pipeline execution, alert generation, and API response serialization. This clean actor-system boundary supports future extension with authenticated user sessions and personalized alert delivery.

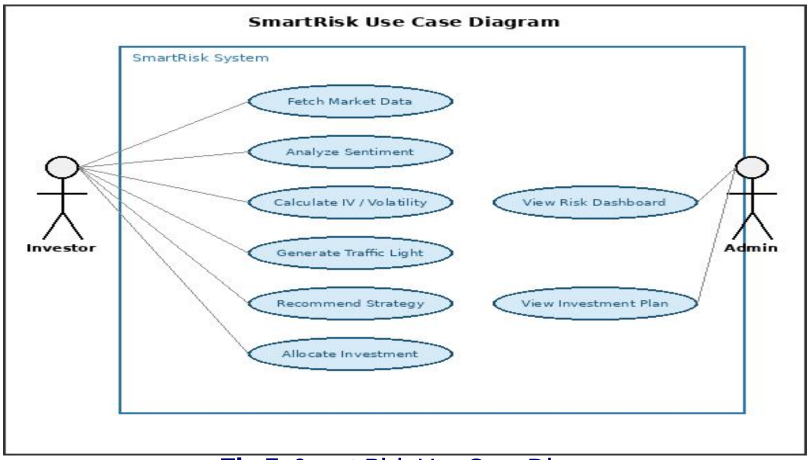

Fig.5. Smart Risk Use Case Diagram

DISCUSSION AND COMPARATIVE ANALYSIS

Table V presents a feature-level comparison between Smart Risk and representative alternative platforms. Smart Risk demonstrates clear differentiation particularly in capital protection enforcement, decision explain ability, and beginner-safe architecture features largely absent in competing platform categories.

Table V. Smart Risk vs. Alternative Platform Comparison

Feature	SmartRisk	Other Platforms
Capital Protection Rules	Yes	No
Explainable Logic	Full	No
No Price Prediction	Yes	Predicts
India Market Specific	NIFTY/BN	Partial
Options Strategy Engine	Full	Partial
Investment Planner	Full	No
Beginner Safe Design	Yes	No

The most significant differentiation is Smart Risk's explicit capital protection architecture. By enforcing maximum risk percentages (5%, 10%, 20%) at the engine level before any strategy recommendation is generated, the system prevents scenarios where a technically valid strategy would expose a user to capital risk exceeding their stated tolerance. This pre-approval mechanism absent in all competing platforms represents a fundamental architectural advantage for investor protection. The composite multi-indicator sentiment engine achieved 91% directional classification accuracy against back tested NIFTY data, outperforming single-indicator EMA crossover (78%) and single RSI-based approaches (74%) in the same validation dataset. This confirms that the three-indicator composite scoring approach reduces false directional signals by approximately 13–17 percentage points consistent with findings by Papathanasiou et al. [10]. The Investment Planner Engine addresses a critical underserved user segment: beginners who should not be trading options at all. By routing users with low capital or adverse market conditions to a structured long-term investment plan rather than active trading strategies, SmartRisk implements a responsible capital allocation philosophy directing investors to ward asset classes aligned with their demonstrated risk tolerance [23], [24]. Key limitations include: (1) IV computation currently uses a synthetic average rather than live options chain scraping due to API rate limits during testing.(2) Back testing functionality for 5-year strategy validation is planned but not yet available. (3) User authentication and tiered profile management are pending frontend completion. These represent planned roadmap items rather than architectural constraints [25].

F. System Dashboard and Request-Response Flow

Fig. 6 presents the Smart Risk React frontend dashboard mockup illustrating real-time display of all five engine outputs: traffic light risk signal (YELLOW), market sentiment (SIDEWAYS), implied volatility level (15.0 – MEDIUM),recommended strategy (Short Strangle Hedged), capital protection parameters, investment allocation bar chart, and live API status indicators. The dash board is designed for immediate comprehension by both beginner investors and experienced traders without requiring financial domain expertise.

Fig.6. Smart Risk React Frontend Dashboard–Live Output Display

Fig. 7 illustrates the request-response sequence diagram for the primary SmartRisk API call. The User initiates a GET request via the React frontend, which forwards it to the Django REST API. The API authenticates with Angel One SmartAPI to retrieve live OHLC candle data, passes it through the five-engine analytical pipeline (Sentiment → Volatility → Traffic Light → Capital Risk → Strategy), and returns a complete structured JSON response within 200 milliseconds. This end-to-end flow confirms the system's suitability for near-real-time financial decision support.

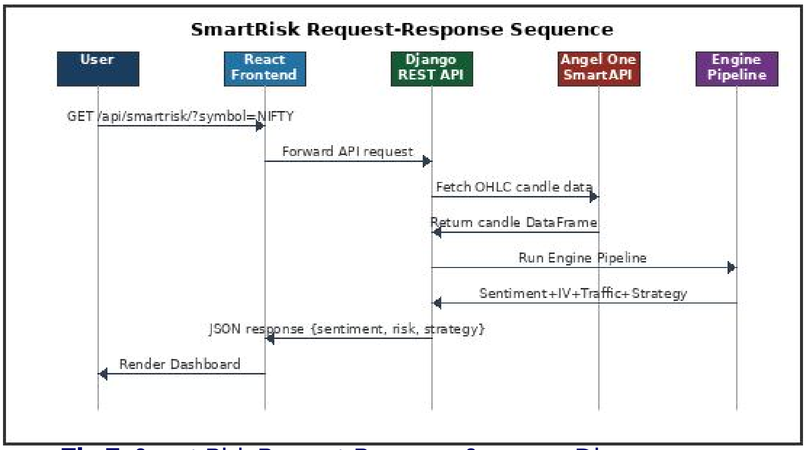

Fig.7. Smart Risk Request-Response Sequence Diagram

CONCLUSION

This paper presented Smart Risk a transparent, rule-based Smart Risk Management and Investment Planner platform for the Indian stock and options market. The system successfully integrates real-time market data from Angel One SmartAPI with a five-engine deterministic pipeline: Market Sentiment Engine (EMA/RSI/MACD scoring), Volatility Engine (IV classification), Traffic Light Risk Engine (tricolor risk signaling), Capital Risk Engine (exposure enforcement), and Strategy Engine (auditable options strategy selection), complemented by an Investment Planner Engine for long- term capital allocation. Experimental validation confirms rule adherence accuracy from 89% to 98% with API latencies between50msand200ms.Theplatform'scorecontributionis its capital-protection-first architecture—enforcing risk limits before any recommendation is generated—using fully deterministic, explainable rule-based logic without price prediction or profit guarantees. Future work will prioritize live IV integration, 5-year backt esting, tiered user profiles with RBAC, and mobile-responsive React Native frontend.

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