

# ContraNova: The Contraview BioCapital Engine

An Autonomous, On-Chain, Data-Driven Platform for Biotech Investment

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**Abstract**—Current biotech investing is inefficient and biased. Decisions are often made behind closed doors and guided by hype rather than scientific merit. As a result, capital fails to reach the most transformative innovations. ContraNova, developed by Contraview, is an autonomous intelligence layer that uses rigorous, data-driven analysis to allocate capital. The system is designed to be transparent and auditable via blockchain. ContraNova focuses on scientific potential rather than short-term trends, with the goal of outcompeting traditional investors and funding breakthroughs that private and public markets have historically missed.

**Index Terms**—Biotech investing, knowledge graphs, autonomous agents, valuation modeling, blockchain, on-chain analytics, due diligence

## I. INTRODUCTION: MARKET NEED AND INDUSTRY PAIN POINTS

Biotechnology is at an inflection point: breakthroughs in synthetic biology, gene editing, and precision medicine can tackle vast unmet needs and have already demonstrated speed at scale (e.g., mRNA vaccines) [1]. Yet capital formation lags the science, and VC decisions often lean on pattern-matching and non-auditable judgment [2], [3], leading to slow insight loops, misallocation, and underfunded breakthroughs in a market primed for trillion-scale growth.

### A. Our Remedy

We propose an **AI-native, on-chain** investing platform that makes biotech capital allocation rigorous and transparent. An AI diligence engine synthesizes genomic, clinical, human, and market data to score scientific merit and product–market fit. Standardized, auditable scorecards and blockchain smart contracts provide transparent, milestone-based funding and immutable record keeping. Continuous post-investment monitoring closes the loop, surfacing risks early and compounding learning across the portfolio.

## II. TECHNICAL ARCHITECTURE

The platform operates continuously in discrete time periods, where  $t$  represents the current period (e.g., weekly) and  $t+1$  the subsequent period.

### A. Data Aggregation and Knowledge Graphs

A multi-source data aggregation engine feeds a dynamic knowledge-graph stack [4].

- **Automated Data Crawling:** At each time step  $t$ , the system performs a comprehensive crawl of the biotechnology web to capture the latest data points:

$$X_{\text{crawl}}(t) = \{x_i \mid x_i \in \text{Web}_{\text{biotech}} \text{ at time } t\}.$$

- **AI-Driven Synthesis:** Public and proprietary data populate two evolving knowledge graphs,  $G_{\text{public}}(t)$  and  $G_{\text{private}}(t)$ . An autonomous agent system inspired by the BabyAGI framework [5] executes a synthesis function  $f_{\text{AGI}}$  to derive higher-order insights for  $t+1$ :

$$M_{t+1} = f_{\text{AGI}}(G_{\text{public}}(t), G_{\text{private}}(t)).$$

- **Latent Representation (Expert Checklist):** Convert aggregated and synthesized signals into a  $d$ -dimensional latent representation using a Contraview-defined expert one-hot checklist of field-important variables. This yields

$$Z(t) \in \{0, 1\}^d,$$

where  $d$  is set based on expert grasp of critical variables and is used as input to downstream models.

### B. Human Capital Assessment

A proprietary database compiles structured data on key personnel—including research profiles, education, investment history, and network overlaps—to algorithmically quantify team strength, a critical driver in biotechnology ventures.

### C. Autonomous AI and Continuous Learning

Predictive models adapt autonomously. At the end of each period, parameters update via gradient descent to minimize predictive error against the newly aggregated dataset  $X_t$ :

$$\theta_{t+1} = \theta_t - \alpha \nabla J(\theta_t, X_t),$$

where  $\alpha$  is the learning rate and  $\nabla J$  is the gradient of the cost function.

### D. Rigorous Backtesting and Benchmarking

Predictive accuracy is validated by backtesting AI-generated valuations against public (Wall Street) and private (Pitchbook) benchmarks for each time period  $t$ .

- **Predictive Accuracy Score:** Mean squared error (MSE) between the model valuation  $\hat{V}_{\text{model}}(t)$  and the verified valuation  $V_{\text{actual}}(t)$ :

$$\text{Score}_{\text{predictive}}(t) = \frac{1}{n} \sum (\hat{V}_{\text{model}}(t) - V_{\text{actual}}(t))^2.$$

### E. Blockchain Integration and Human Value Scoring

To enable radical transparency and objective measurement of value drivers:

- **On-Chain Transparency:** A cryptographic hash of each period's predictive score and associated metadata is published on-chain:

$$S_{\text{chain}}(t) = \text{Hash}(\text{Score}_{\text{predictive}}(t), \text{Metadata}).$$

- **Human Value Score (HVS):** The impact of any human-in-the-loop contribution (e.g., advisory input) is quantified via a weighted average:

$$\text{HVS} = \frac{\sum_{i=1}^m (\alpha_i \cdot \text{Score}_{\text{human},i})}{\sum_{i=1}^m \alpha_i},$$

where weights  $\alpha_i$  reflect empirically validated impact.

## III. TOKENOMICS AND ENGAGEMENT

Details on the tokenomics model and our strategy for engaging with industry stakeholders and the broader community will follow in a subsequent paper. The focus is a sustainable ecosystem that incentivizes participation and aligns all stakeholders toward advancing high-impact science.

## IV. WHERE WE STAND

We have implemented and validated the analytical framework across a substantial dataset, demonstrating strong correlation with established financial benchmarks. The engine has generated in-depth analyses for **100 public and 200 private biotechnology companies**. The expert one-hot checklist latent space is currently  $d = 110$  dimensional.

Predictive performance, measured by coefficient of determination  $R^2$ , aligns with industry-standard human analysis:

- $R^2 = 0.74$  for public companies, benchmarked against Wall Street consensus scores.
- $R^2 = 0.85$  for a combined portfolio of public and private companies, benchmarked against a normalized composite of Wall Street and Pitchbook data.

Our distinction lies in **scale and efficiency**. By requiring zero human capital for the core analytical process, we remove subjective bottlenecks and reduce operating costs, positioning ContraNova to capture outsized market share.

## V. CONCLUSION AND CALL TO ACTION

With core technology validated, we seek strategic investment to scale operations, expand data infrastructure, accelerate market penetration, and broaden human data collection.

This is an opportunity to partner in redefining biotech investment analysis. We are offering equity and/or tokens in exchange for growth capital to fuel the expansion of Contraview.

## REFERENCES

- [1] F. P. Polack, S. J. Thomas, and N. Kitchen, "Safety and efficacy of the bnt162b2 mRNA covid-19 vaccine," *New England Journal of Medicine*, vol. 383, no. 27, pp. 2603–2615, 2020.
- [2] McKinsey Company, "Biotech venture capital: Challenges and opportunities," McKinsey Company, Tech. Rep., 2022. [Online]. Available: <https://www.mckinsey.com/industries/life-sciences/our-insights>
- [3] Grand View Research, "Biotechnology market size, share trends analysis report," 2023. [Online]. Available: <https://www.grandviewresearch.com/industry-analysis/biotechnology-market>
- [4] L. Ehrlinger and W. Wöb, "Towards a definition of knowledge graphs," *CEUR Workshop Proceedings*, vol. 2322, 2019. [Online]. Available: <http://ceur-ws.org/Vol-2322/>
- [5] Y. Nakajima, "Babyagi," <https://github.com/yoheinakajima/babyagi>, 2023.