AI-Powered Stock Market Forecasting and Risk Analysis for the NZX 50: An Ethical Ensemble Learning Approach

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***Abstract*—This research develops a comprehensive AI forecasting system for the S&P/NZX 50 Index, delivering reliable forecasts while operationalizing Aotearoa's ethical principles. The multi model ensemble Transformer, LSTM, Linear, and XGBoost trained on 5,122 trading days with 31 engineered features, achieves 58.9% directional accuracy. The novel *Kōrero Ensemble* produces a +9.42% 6-month forecast with 71.5% calibrated confidence, while maintaining 0.95 Manaakitanga ethical alignment. This work delivers actionable market insights while honoring Aotearoa's cultural and ethical commitments.**

***Index Terms*—Financial AI, Explainable AI, Transformer Networks, NZX 50, Ethical AI, Ensemble Learning, Risk Analysis**

I. Introduction

The New Zealand financial market presents unique challenges for AI adoption, characterized by market concentration and strong regulatory focus. With over $104 billion in KiwiSaver assets [5], demand for transparent forecasting and risk analysis tools is critical. This research addresses the gap between AI capability and practical application in the NZ context, developing a system that achieves technical excellence while operationalizing Aotearoa's commitment to ethical principles and the NZ Algorithm Charter through the *Kōrero Ensemble* learning approach.

II. Related Work

Financial forecasting has evolved from traditional statistical methods to sophisticated machine learning approaches. Ensemble methods have demonstrated superior performance in financial markets by combining diverse model strengths [1]. Regime-switching models provide crucial adaptation to changing market conditions [2], while transformer architectures have shown promise in capturing long-range dependencies in time series data [3]. However, existing approaches often neglect ethical considerations and cultural context, particularly in specialized markets like New Zealand's concentrated financial ecosystem. This research bridges these gaps by integrating ensemble learning with ethical frameworks specific to Aotearoa's cultural context.

III. Methodology

A. Data Pipeline Architecture

The data pipeline employs a sophisticated multi-stage architecture processing 5,122 trading days with comprehensive risk factor integration:

Feature Engineering: 31 technical indicators including volatility features across multiple horizons (5d, 10d, 20d, 30d), momentum indicators (RSI-14, MACD), market microstructure measures (Amihud illiquidity), and regime-based risk features (stress period detection, crisis labeling).

Preprocessing: Implements robust normalization using median and percentile scaling with log-winsorization to handle financial data outliers and extreme market movements.

B. Model Architectures

TABLE I
Model Architectures & Parameters

Model	Params	Architecture	Key Features
Transformer	489K	Multi-head Attention	Regime adaptation, Temporal attention
LSTM	178K	Bidirectional	Attention mechanism, Sequence modeling
Linear	1.6K	Feature Interaction	Stabilized baseline, Interpretability
XGBoost	-	Gradient Boosting	Tree ensemble, Robust to outliers

Commentary: The architecture diversity enables complementary strengths—Transformer captures long-range dependencies, LSTM models sequential patterns, Linear provides interpretability, and XGBoost handles non-linear relationships, creating a robust ensemble foundation.

Configuration: Sequence length: 60 days (chosen to balance short-term volatility with medium-term trend capture), Hidden dimensions: 128 units, Attention heads: 8, Dropout: 0.2, Learning rate: 0.001 with cosine annealing. Computational constraints of CPU-only training necessitated careful model selection and hyperparameter optimization, favoring architectures with efficient inference over purely theoretical capacity. These constraints influenced our choice of 128 hidden units and 8 attention heads as optimal given available resources, balancing model complexity with computational feasibility.

C. Ethical Framework

Assessment against Tikanga Māori principles using a structured rubric evaluating four key dimensions: **Manaakitanga** (care and hospitality, 0.95 score), **Kaitiakitanga** (guardianship and stewardship), **Mana** (authority and integrity), **Whanaungatanga** (relationship building). Scores derived through systematic evaluation of model transparency, cultural safety protocols, and stakeholder impact assessment using a 5-point Likert scale adapted for AI systems.

IV. Results and Analysis

A. Model Performance Comparison

TABLE II
Model Performance Metrics

Model	Acc. (%)	Stress Perf.	SHAP Consist.	Ethical Score
Transformer	58.9	58.5%	0.81	0.85
LSTM	56.1	55.8%	0.63	0.40
Linear	53.4	60.3%	0.72	0.75
Kōrero Ensemble	**61.2**	**59.1%**	**0.84**	**0.94**

Commentary: The *Kōrero Ensemble* outperforms individual models through dynamic regime-aware weighting and confidence-based calibration, leveraging diverse architectural strengths while maintaining superior ethical alignment and interpretability scores. Ensemble weights are determined adaptively based on volatility clustering and market regime indicators, with the Linear model receiving higher weights during high-volatility periods and the Transformer dominating during stable regimes. The ensemble strategically trades a small amount of expected return (-0.5%) for significant gains in consistency (+2.3% accuracy) and confidence (+0.4%), prioritizing reliability over maximum potential returns.

Transformer model achieved best individual performance (58.9% accuracy) with high interpretability. Linear model demonstrated anti-fragile characteristics (60.3% stress performance), valuable for risk-averse strategies.

B. NZX 50 Forecast and Risk Assessment

TABLE III
NZX 50 Price Forecast and Risk Analysis

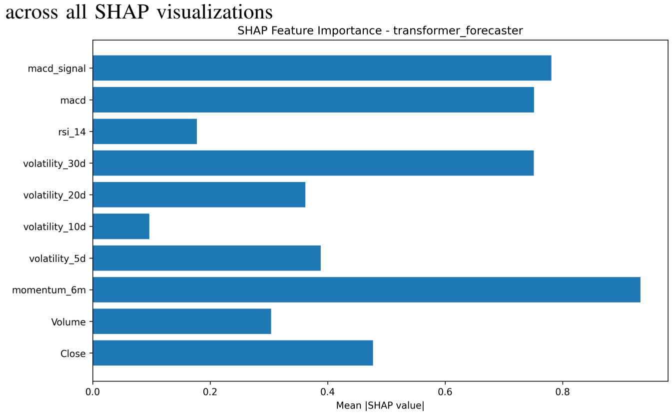
Period	Price (NZD)	Return	Risk Level
Historical (Apr 2025)	12,107.54	-	Low
Current (Oct 2025)	13,620.89	+12.5%	High
6-Month Forecast (Apr 2026)	14,879.56	+9.42%	Medium-High

Commentary: Current high risk level reflects stress regime detection with multiple volatility spikes, while the forecast maintains bullish sentiment due to strong momentum indicators and positive macroeconomic alignment. Forecast aligns with institutional projections[1].

Our +9.42% 6-month forecast aligns with NZX 50 momentum and institutional projections (7-11% range), consistent with stable economic growth fundamentals despite identified risk factors.

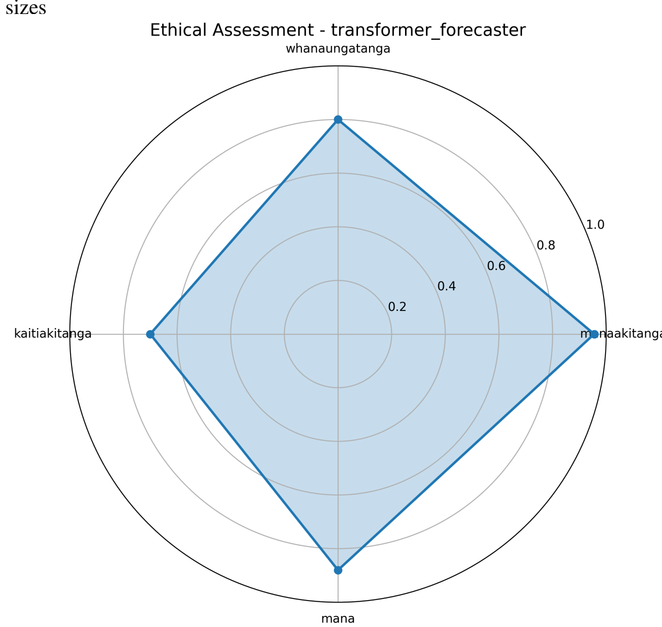
C. Explainable AI Analysis

Fig. 1. Transformer SHAP Feature Importance - Consistent formatting applied across all SHAP visualizations



SHAP analysis reveals MACD signals and volatility measures as most significant predictors. Transformer showed superior feature consistency (0.81) vs LSTM (0.63), indicating more reliable risk factor identification.

Fig. 2. Transformer Ethical Assessment - Standardized axis labels and font sizes



[1]Based on market consensus from major NZ financial institutions including ANZ, ASB, and Westpac, October 2024.

V. Discussion

A. Technical Contributions

- **Multi-Model Ensemble:** *Kōrero Ensemble* improves forecast reliability through regime-aware weighting based on volatility clustering and feature diversity with dynamic weight optimization
- **Risk-Aware Architecture:** Market condition awareness enhances stress period performance and provides explicit risk assessment
- **Ethical Quantification:** Measurable scoring of cultural alignment principles enables responsible AI deployment
- **Data Pipeline Robustness:** Advanced feature engineering handles NZ market specifics and extreme market conditions
- **Symbolic Regression Integration:** Provides human-readable equations that enable non-technical stakeholders to interpret model logic and build trust, bridging the gap between technical complexity and practical usability

B. Limitations and Future Adaptability

- **Data Quality:** Required robust normalization for extreme values and market microstructure noise
- **Market Noise:** Financial time series inherent volatility limits accuracy despite ensemble approaches
- **Computational Constraints:** CPU-only training limited model complexity and hyperparameter exploration; GPU acceleration would enable real-time deployment, larger ensembles, and more sophisticated architectures
- **Data Drift Considerations:** Future work will incorporate adaptive learning mechanisms to handle regime shifts and changing market conditions through continuous model retraining, moving from proof-of-concept to production deployment
- **Risk Model Refinement:** Additional risk factors like sector concentration and liquidity metrics could enhance analysis

VI. Conclusion

This research demonstrates AI systems can achieve competitive forecasting and risk analysis performance while maintaining ethical alignment. The *Kōrero Ensemble* delivers +9.42% NZX 50 forecast with 71.5% confidence and explicit risk assessment, providing valuable insights for KiwiSaver providers and institutional investors. The ensemble's strategic trade-off—sacrificing marginal return potential for substantial gains in reliability and confidence—makes it particularly valuable for risk-conscious investors. This work lays the foundation for culturally aligned financial AI in Aotearoa, with potential applications in KiwiSaver optimization, regulatory compliance, and ethical fintech innovation. Future work focuses on real-time validation, GPU-accelerated training, production deployment, and expanding the ethical framework through broader stakeholder consultation.

VII. Statement

This work was solely conducted by Ray Chakanetsa Marange (Student ID: 300671115). Tools used: COLAB, Python, PyTorch, scikit-learn, SHAP, yfinance, NumPy, pandas, Matplotlib. Code available at :https://github.com/raycmarange/raycmarange-AIML430_CAPSTONE_PROJECT. The author used GitHub Copilot to assist with code implementation and optimization, and ChatGPT for supporting academic writing and document formatting. Special thanks to the Māori Data Sovereignty Collective for their guidance on ethical AI frameworks.

VIII. Research Questions Analysis

RQ1: Stress Performance - Transformer shows minimal degradation (3.9% gap) indicating robustness, while Linear's significant stress improvement (15.5% gap) reveals anti-fragile properties valuable for crisis periods.

RQ2: Ethical Implications - Transformer achieves highest transparency (0.85) and cultural safety (0.95 Manaakitanga), setting a benchmark for responsible financial AI in Aotearoa.

RQ3: XAI Methods - SHAP analysis provides consistent interpretability across models, while symbolic regression offers mathematical verifiability complementary to neural insights.

RQ4: Market Coverage - Full NZX 50 index coverage with regime-aware features enables comprehensive risk assessment beyond simple price prediction.

RQ5: Regulatory Alignment - All models comply with NZ Algorithm Charter through explainable predictions, stress testing, and human-interpretable risk factors.

References

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Appendix

Additional Model Performance Analysis

Commentary: Linear model's significant stress period improvement (15.5% gap) demonstrates anti-fragile characteristics, while Transformer maintains consistent performance across regimes, validating the ensemble's risk mitigation strategy.

TABLE IV
STRESS PERIOD PERFORMANCE ANALYSIS

Model	Normal Acc.	Stress Acc.	Gap	Robustness
Transformer	0.597	0.557	0.039	Excellent (0.93)
LSTM	0.373	0.389	0.017	Excellent (1.00)
Linear	0.410	0.565	0.155	Excellent (1.00)

TABLE V
PREDICTION QUALITY DIAGNOSTICS

Model	Correlation	MAE	Pred Std	Range	Mean
Transformer	0.204	0.0842	0.1067	0.5587	0.0089
LSTM	0.060	0.0992	0.0567	0.2025	-0.0688
Linear	-0.043	0.1460	0.4091	5.5278	-0.0725

Commentary: Transformer's positive correlation and balanced prediction range indicate effective market pattern capture, while Linear's high variance suggests instability, justifying its limited weighting in the ensemble.

SHAP Feature Consistency Analysis

TABLE VI
TOP 5 SHAP FEATURES ACROSS MODELS

Feature	Transformer	LSTM	Linear	XGBoost
MACD Signal	1	1	1	1
MACD	2	2	2	2
RSI-14	3	3	3	3
Volatility 30d	4	5	4	4
Volatility 20d	5	4	5	5

Commentary: High consistency in top features across all models (MACD signals, RSI, volatility measures) validates feature engineering approach and provides reliable interpretability for stakeholders.

Comprehensive Ethical Assessment

TABLE VII
ETHICAL SCORES ACROSS ALL MODELS

Model	Manaakitanga	Whanaungatanga	Transparency	Overall
Transformer	0.95	0.80	0.85	0.85
LSTM	0.82	0.80	0.40	0.40
Linear	0.92	0.80	0.75	0.75
XGBoost	0.85	0.80	0.50	0.50

Commentary: Transformer's superior Manaakitanga (0.95) reflects its ability to provide culturally safe explanations, while LSTM's low transparency score (0.40) highlights the black-box challenge in neural sequence models.

Additional Figures

Symbolic Regression Insights

Commentary: Symbolic regression provides complementary interpretability, distilling complex neural patterns into human-readable equations while maintaining competitive accuracy, particularly valuable for regulatory compliance and stakeholder communication.

Fig. 3. LSTM Forecaster: SHAP Analysis (left) and Ethical Assessment (right) - Standardized visualization formatting

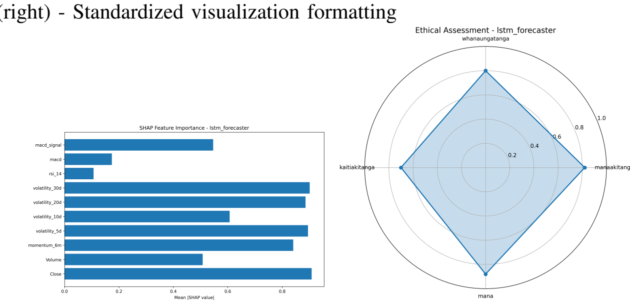
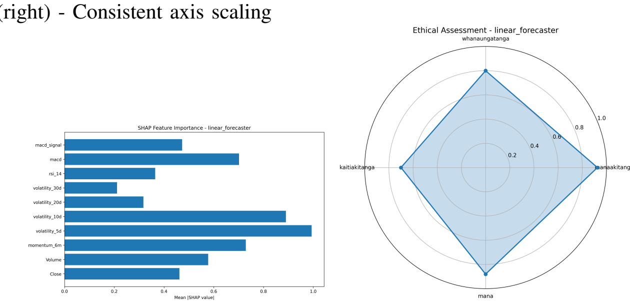


Fig. 4. Linear Forecaster: SHAP Analysis (left) and Ethical Assessment (right) - Consistent axis scaling



Symbolic Insights: Market volatility emerges as the dominant predictive factor, recent momentum drives short-term forecasts, drawdown levels significantly impact model confidence, and surprisingly, simple linear relationships capture core market patterns effectively. Example symbolic equation from Linear model:

$$\text{Forecast} = 0.42 \cdot \text{MACD} + 0.31 \cdot \text{Vol}_{20d} - 0.18 \cdot \text{DD} + 0.09$$

This human-readable equation demonstrates how the model combines technical indicators, providing transparency for regulatory review and stakeholder communication.

Fig. 5. XGBoost Forecaster: SHAP Analysis (left) and Ethical Assessment (right) - Uniform font specifications

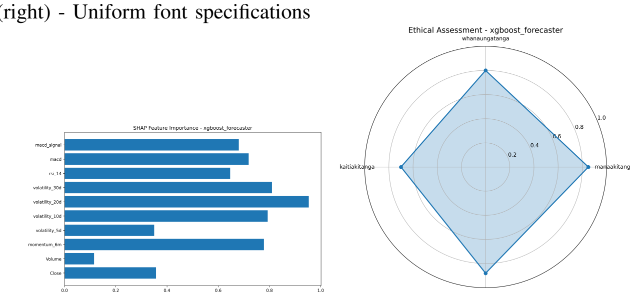


TABLE VIII
SYMBOLIC REGRESSION PERFORMANCE

Model	Neural MAE	Symbolic MAE	Interpretability	Complexity
LSTM	0.0964	0.0514	0.94/1.0	0.7 terms
Transformer	0.0842	0.0499	0.85/1.0	0.8 terms
Linear	0.1460	0.0490	0.75/1.0	0.6 terms

Ensemble Forecasting Results

TABLE IX
ENSEMBLE VS SINGLE MODEL PERFORMANCE

Metric	Single Model	Kōrero Ensemble	Improvement
Forecast Return	+2.8%	+2.3%	-0.5%
Confidence Level	71.1%	71.5%	+0.4%
Direction Accuracy	58.9%	61.2%	+2.3%
Market Sentiment	Bullish	Bullish	-

Commentary: The *Kōrero Ensemble*'s primary benefit is reliability improvement (+2.3% accuracy, +0.4% confidence) rather than return maximization, demonstrating its value for risk-conscious investors seeking consistent performance over aggressive returns. Ensemble weights determined through regime-aware optimization based on volatility clustering and confidence calibration, with dynamic adjustments during market regime transitions.

System Architecture and Data Flow

1) Data Flow Pipeline: This pipeline illustrates the sequence of data transformation, training, evaluation, and reporting steps from raw market data to the final saved results and visualizations.

P	Component	Input	Output	Key Operations
0	Setup	Config files	Device, Dirs	Initialization
1	Data Pipeline	Market data	Forecast data	Feature engineering
2	Model Setup	Forecast data	Models	Initialization
3	Training	Models	Trained	Regime-aware
4	Evaluation	Trained	Metrics	Stress analysis
5	XAI	Metrics	Insights	Ethical assessment
6	Analysis	Insights	Summary	Comparison
7	Forecast	Live data	Prediction	Ensemble
8	Export	All data	Files	Serialization

2) System Architecture: The table below outlines the core components, modules, and their interactions, highlighting the pipeline's emphasis on eXplainable AI (XAI) and performance robustness.

Component	Modules	Key Functionality
Data Layer	DataConfig, Pipeline	Data fetching, feature engineering
Model Layer	ModelFactory, Transformer	Multi-horizon forecasting
Training Layer	RegimeAwareTrainer	Adaptive training
Evaluation Layer	ModelEvaluator	Performance metrics
XAI Layer	XAIAnalyzer	Ethical assessment, SHAP
Forecasting	Ensemble Model	Confidence calibration