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GARCH Model Hybridization with Feed Forward Neural Network Algorithm Approach for Predicting The Volatility of The Composite Stock Price Index

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ABSTRACT

Stock market volatility is a crucial indicator in measuring investment risk and influencing investor decision-making, where proper understanding of volatility movements can help investors optimize their investment portfolios. Time series data from stock exchanges show complex heteroscedasticity characteristics, where volatility levels can change dynamically over time, creating distinct challenges in modeling and prediction. The implementation of the hybrid model is carried out by integrating the advantages of both models, where GARCH (Generalized Autoregressive Conditional Heteroscedasticity) is used to capture volatility clustering characteristics, while FFNN (Feed Forward Neural Network) is utilized to capture complex non-linear patterns in the data. By using evaluation of several comprehensive error measurement metrics, including Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE), to ensure model reliability in various aspects of prediction. The use of the GARCH-FFNN hybrid model is expected to provide more accurate volatility predictions compared to using GARCH or FFNN models separately, with potential improvements in prediction accuracy and adaptability to changing market conditions. These findings provide important contributions to stock market volatility modeling and can serve as a reference for investors, portfolio managers, and financial practitioners in making better investment decisions, as well as paving the way for the development of more sophisticated volatility prediction models in the future.

Keywords: GARCH, FFNN, forecasting, hybridization, IDX (Indonesia Stock Exchange) Composite, stock volatility

1. Introduction

The economic conditions of a country experience fluctuations influenced by various internal and external factors, which significantly impact the behavior of capital market participants in analyzing and predicting their investment performance [1]. Financial market time series data, particularly stock exchange and other financial data, typically exhibit distinctive characteristics, namely the presence of volatility or heteroscedasticity in their patterns. Financial markets play a crucial role in a country's economy, including Indonesia, where one of the activities chosen by investors is investing, particularly in stocks. In stock investment, there exists a volatility phenomenon, a situation where stock price values experience both increases and decreases, making volatility in financial markets particularly attractive to investors due to its impact on global financial markets [2].

Volatility can be defined as the level of fluctuation in asset prices, where prices can rise or fall over time. In many cases, volatility is characterized by periods of low fluctuations, followed by periods of high fluctuations, and vice versa. This demonstrates that volatility is not constant over time but rather exhibits clustering behavior. Estimating volatility as accurately as possible is essential because investment returns can be derived from volatility, and asset prices can be calculated based on these returns [3]. The volatility of asset returns can be modeled using time series models that capture these temporal dependencies and patterns in the data.

In recent years, academics and financial analysts have shown increasing interest in modeling and forecasting financial time series volatility due to its influence on many economic and financial applications. One important

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phenomenon related to volatility is the negative correlation between stock returns and volatility, known as asymmetric volatility [4]. The leverage effect, where a decrease in stock value (negative return) increases financial leverage, can also lead to increased volatility [5]. Negative news often has a greater impact on the conditional variance of equity returns compared to positive news due to this leverage effect. Stock market volatility is also closely related to asset risk, making it an essential measure for risk assessment in investment decision-making [6].

To address the heteroscedasticity problem in time series data, several models have been developed, including the ARCH (Autoregressive Conditional Heteroscedastic) model introduced by Engle (1982) and later expanded by Bollerslev (1986) into the more general GARCH model [7]. The GARCH model allows for Autoregressive and Moving Average components with heteroscedastic variance within its structure. The GARCH structure consists of two equations: the conditional mean equation, which is the standard ARCH model, and the conditional variance equation, which allows variance to change over time. Many stock volatility studies have used the GARCH model, including comparisons of GARCH model performance in capturing stock market volatility across various countries and research on stock price volatility prediction using GARCH [8].

One of the forecasting methods currently developing is the use of Artificial Neural Networks (ANN), particularly the FFNN model [6]. ANNs have the ability to learn and adapt to new situations by remembering past data patterns, even when there is noise in the data. The FFNN model consists of input layers, hidden layers, and output layers, with processing elements called neurons [9]. In FFNN, the number of neurons in the hidden layer affects the model's ability to minimize error, with more neurons allowing greater flexibility in adapting to current data [10]. Beyond the number of parameters used, varying estimation methods, such as the backpropagation algorithm, also influence the performance of the feed forward neural network model, making it suitable for handling complex and fluctuating time series data.

The development of investment opportunities is not only indicated by the increasing number of investments or investors but also by the growing number of alternative investment instruments available to investors. To achieve investment objectives, it is important for investors to understand the concepts of return and risk that accompany investment activities [11]. Return is the expected profit, while risk is the possibility of differences between actual returns and expected returns. These two concepts are interconnected, requiring investors to consider both aspects when investing. Stock price fluctuations are influenced by many factors, making them difficult to understand and formulate mathematically [12]. However, by observing the patterns of past stock price movements, it becomes apparent that these movements often repeat, allowing these patterns to be recognized and used to predict future stock price movements, which is the fundamental basis for time series prediction models.

Another approach to improve forecasting accuracy is the integration of FFNN with Genetic Algorithms (GA) [13]. The FFNN model offers flexibility in selecting model inputs and the number of hidden units used, allowing for various data analyses with desired outputs, including time series data analysis. Using FFNN in time series forecasting can be a good solution, but the challenge lies in determining the appropriate network architecture and training method [14]. GA is particularly well-suited for solving combinatorial problems that require extensive computation time. Therefore, the integration between FFNN and GA for time series forecasting can leverage the advantages of both methods [15]. Case studies have shown that the combination of ANN and GA provides more accurate results for time series forecasting compared to conventional methods, offering a promising approach for predicting stock price volatility in the Indonesian Composite Stock Price Index (IHSG) and other financial markets, which is essential for investors to make informed investment decisions in fluctuating market conditions [9].

The present study provides several important contributions to the field of financial volatility modeling and prediction. Integrating the volatility clustering capabilities of EGARCH (Exponential Generalized Autoregressive Conditional Heteroscedasticity) with the non-linear pattern recognition strengths of Feed-Forward Neural Networks by develops a novel parallel processing EGARCH-FFNN hybrid model. Developing a sophisticated feedback loop mechanism between components that enables real-time interaction and mutual refinement of predictions. By implements a comprehensive Genetic Algorithm optimization framework that simultaneously optimizes both EGARCH parameters and FFNN architecture while introducing adaptive window sizing functionality that automatically adjusts historical data windows based on detected market regime changes provides the first comprehensive 10-year volatility analysis of the Indonesian Composite Index (IHSG) using hybrid econometric-machine learning approaches, incorporating Indonesia-specific market microstructure factors including Ramadan effects, Chinese New Year impacts, and emerging market characteristics. The research develops methodological innovations including an attention mechanism within the neural network architecture to automatically focus on relevant temporal patterns, implements regime-based evaluation frameworks that assess model performance across different market conditions, and introduces dynamic feature engineering that adapts to changing market conditions. The model delivers a practical implementation framework with comprehensive evaluation using multiple error metrics (RMSE, MAE, MAPE, R-squared), detailed guidelines for real-world implementation including computational requirements and integration procedures with existing risk management systems, and establishes adaptive threshold frameworks for early warning systems in volatile markets. These contributions advance both theoretical understanding of hybrid volatility modeling and provide practical tools for investors, portfolio managers, and financial practitioners operating in emerging markets, particularly in the Indonesian context.

2. Related Works

Several previous studies have explored various approaches to modeling financial time series volatility, particularly focusing on the integration of neural networks with traditional econometric models.

Yasin and Suparti from the Department of Statistics at FSM UNDIP conducted research titled "Volatility Modeling for Value at Risk (VaR) Calculation Using Feed Forward Neural Network and Genetic Algorithm", utilizing PT. Indofood Sukses Makmur Tbk stock price data with a focus on stock return data [10]. This study combined several methods, namely the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model, Feed Forward Neural Network (FFNN), and Genetic Algorithm (GA) as a training algorithm, subsequently referred to as the GA-Neuro-GARCH model. The research process began with initial modeling using ARIMA(1,0,1)-GARCH(1,1), the results of which were then used as inputs for the FFNN model. The FFNN architecture employed consisted of 2 neuron units in the input layer, 5 neuron units in the hidden layer, and 1 neuron unit in the output layer. To optimize the FFNN weights/parameters, a Genetic Algorithm was utilized with a population size of 50 chromosomes, single-point crossover, mutation probability of 0.01, and 5000 generations. The results demonstrated that the best model was obtained with a crossover probability of 0.4, yielding an excellent accuracy level with a MAPE of 0.0039%. This GA-Neuro-GARCH model successfully demonstrated good performance in modeling stock return volatility and could be used to calculate Value at Risk (VaR) with a 95% confidence level, proving that the combination of the GARCH model with FFNN optimized using Genetic Algorithm represents a viable alternative for modeling stock return volatility, with very high accuracy levels.

In another comparative study, researchers evaluated two models: Feed Forward Neural Network (FFNN) and Generalized Autoregressive Conditional Heteroscedasticity (GARCH) in predicting time series data, specifically on the Jakarta Stock Exchange Composite Index (IHSG) data from January 2, 2007, to May 12, 2010 [16]. The dataset was divided into two parts, with 767 data points used for model building and 66 data points for model testing. For the FFNN model, researchers employed the Levenberg-Marquardt training method with a logistic sigmoid activation function and implemented the Optimal Brain Damage (OBD) pruning method to obtain an optimal network architecture. In its implementation, the FFNN model initially used 13 input units (lags 1-13) with 10 units in the hidden layer, which after the OBD pruning process, reduced to 7 inputs (lags 2, 3, 7, 9, 10, 11, and 13) and 4 hidden layer units [17]. Meanwhile, for the GARCH model, the analysis results indicated that the best model was GARCH(1,0) or ARCH(1). The comparison results of both models showed that the FFNN model provided better prediction results than the GARCH model, with a training RMSE of 26.55789 and testing RMSE of 41.976691 for FFNN with OBD pruning, compared to a training RMSE of 36.28397 and testing RMSE of 222.2522 for the GARCH(1,0) model [18]. Additionally, the OBD pruning process proved effective in enhancing FFNN network performance by reducing the number of parameters from 151 to 20, resulting in a simpler architecture while still delivering more accurate prediction results.

Research has also been conducted focusing on modeling portfolio return volatility using a combination of Feed Forward Neural Network (FFNN) model with GARCH inputs [6]. The dataset used was daily closing price data of stocks from two companies listed in LQ45, namely PT Bumi Serpong Damai Tbk (BSDE) and PT H.M. Sampoerna Tbk (HMSP) during the period from November 14, 2016, to January 18, 2018. The methodology employed combined several techniques, beginning with portfolio formation using Mean Variance Efficient Portfolio (MVEP), which yielded optimal weights of 46.3% for BSDE and 53.6% for HMSP followed by ARIMA modeling for portfolio returns where the best model obtained was ARIMA(1,0,1). After discovering heteroscedasticity effects through the Lagrange Multiplier test, GARCH modeling was performed, and ARIMA(1,0,1) GARCH(1,1) was determined as the best model. This model was then used as input for FFNN with an architecture consisting of two input units (σ^2t-1 and a^2t-1), ten hidden layer units, and one output unit [19]. The research results indicated that the FFNN model with GARCH input provided excellent performance with a training Mean Squared Error (MSE) value of 6.38 x 10-10 and testing MAPE of 1.14441%, indicating very accurate forecasting capability for modeling portfolio return volatility.

Recent advances in deep learning have significantly enhanced financial volatility modeling capabilities, with several breakthrough studies emerging in the past three years. Aswini Kumar Mishra et al, introduced volatility forecasting and assessing risk of financial markets using multi-transformer neural network based architecture [19], conducted a comprehensive study evaluating hybrid neural network models for volatility forecasting across six financial assets (Euro-USD, AUD-USD, S&P 500, FTSE 100, Reliance Industries, and Samsung Electronics) from January 2005 to December 2021. Their research demonstrated that Transformer-based hybrid models, particularly Multi-Transformer-GARCH (MT-GARCH) and Multi-Transformer-LSTM-GARCH (MTL-GARCH), consistently outperformed traditional GARCH models and individual neural network approaches. The study employed a rolling window methodology with 500 trading days and utilized RMSE and MAE as primary evaluation metrics. Results showed that MT-GARCH achieved superior performance with RMSE values ranging from 2.95×10^{-5} to 1.85×10^{-4} across different assets during the test period (2017-2021), while traditional GARCH models exhibited significantly higher error rates, particularly during volatile periods such as the COVID-19 pandemic in 2020. The incorporation of attention mechanisms and bagging techniques in Multi-Transformer architectures effectively reduced variance in noisy financial data, leading to more accurate volatility predictions. The study's findings align with growing literature on hybrid models, confirming that combining neural networks with traditional econometric methods enhances forecasting accuracy across various market conditions and asset types.

Peng et al. (2024) developed an innovative approach for high-frequency cryptocurrency trend prediction by combining attention-based CNN-LSTM architecture with a novel triple trend labeling methodology [20]. The authors addressed the challenge of excessive trading transactions in high-frequency environments by replacing original price series with local minimum series and implementing a stable triple classification system (increase, decrease, stable) rather than traditional binary classification. Their Attention-based CNN-LSTM model for Multiple Cryptocurrencies (ACLMC) incorporates weight-sharing encoders to extract features across different frequencies and currencies, utilizing attention mechanisms to explore correlations between various cryptocurrency data and frequency patterns. The experimental results on five major cryptocurrencies (BTC, ETH, BNB, XRP, ADA) from 2020-2022 demonstrated that their approach significantly outperformed traditional baseline methods in financial metrics while substantially reducing the number of transactions, achieving better Sharpe ratios and lower maximum drawdown compared to conventional buy-hold and long-short trading strategies. This study highlights the effectiveness of combining advanced deep learning architectures with sophisticated labeling techniques for volatile financial time series prediction.

These studies collectively demonstrate the effectiveness of hybrid approaches that combine traditional econometric models like GARCH with advanced machine learning techniques such as Feed Forward Neural Networks and optimization methods like Genetic Algorithms. The integration of these methodologies has consistently shown superior performance in modeling and forecasting financial time series volatility compared to using individual models alone, particularly when appropriate architecture optimization techniques are employed.

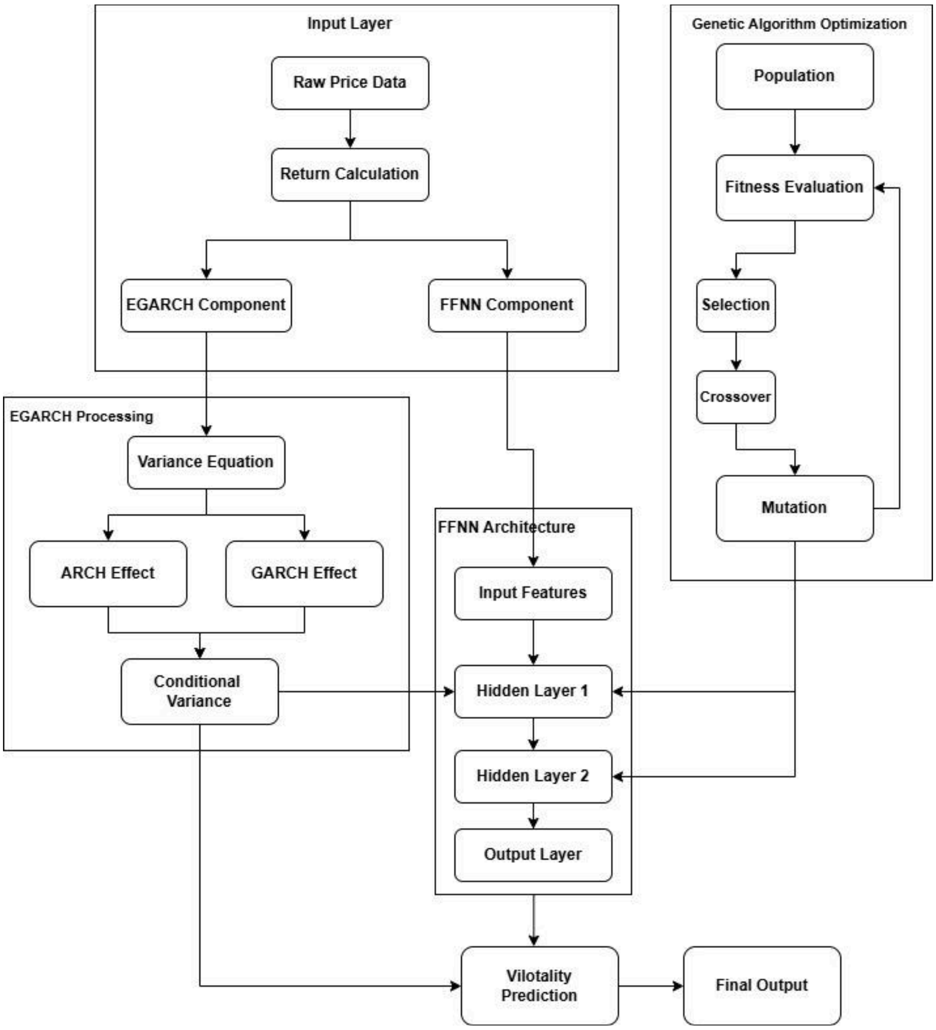

Fig. 1: EGARCH-FFNN Model Optimization With Genetic Algorithm

3. Methodology

This study aims to develop an innovative hybrid approach for predicting stock market volatility by integrating Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) and Feed-Forward Neural Network (FFNN) components, optimized through Genetic Algorithms. As illustrated in Fig. 1, the methodology begins with raw price data collection from various markets, followed by return calculation that serves as input for both the EGARCH and FFNN components [21]. The EGARCH processing path captures market volatility dynamics through variance equations that model both ARCH and GARCH effects, ultimately producing conditional variance estimates. Simultaneously, the FFNN architecture processes input features through two hidden layers, with the network's structure optimized using a Genetic Algorithm framework that employs population initialization, fitness evaluation, selection, crossover, and mutation operations to determine optimal hyperparameters [22]. This parallel processing design allows the conditional variance from EGARCH to inform the hidden layers of the neural network, creating a sophisticated feedback mechanism. The final output combines both model components to generate more accurate volatility predictions than either method could achieve independently [23]. This study represents a significant advancement in financial time series forecasting by leveraging both the statistical power of EGARCH for capturing asymmetric volatility and the non-linear pattern recognition capabilities of neural networks, with evolutionary optimization ensuring the model architecture is finely tuned to the specific characteristics of the financial data being analyzed.

3.1. Dataset

The dataset consists of daily trading information from the Indonesian Composite Stock Price Index (IHSG) and selected companies listed on the Indonesian Stock Exchange (BEI), covering a ten-year period from August

Table 1: IHSG Yahoo Finance Sample Data.

Date	**Open**	**High**	**Low**	**Close**	**Volume**	**Return**
22/10/2019	977.23	982.91	971.07	982.91	1008224300	-
23/10/2019	982.4	992.12	977.16	992.12	1272204200	0.009327
24/10/2019	995.78	1011.91	994.49	1011.46	1579873700	0.019306
25/10/2019	1012.14	1012.65	989.65	991.31	1143236800	−0.02012
28/10/2019	991.99	996.8	988.94	993.58	895389700	0.002287
29/10/2019	993.67	997.85	989.6	997.85	1319622500	0.004288
30/10/2019	1002.26	1002.42	992.72	999.01	1021417400	0.001162

2014 to July 2024 shown in Table 1 as an example. This extensive timeframe was deliberately chosen to capture various market conditions, including both high and low volatility periods, thereby ensuring the model's robustness across different market scenarios. For each trading day, the collected data encompasses six key variables: opening price, highest price, lowest price, closing price, adjusted closing price (accounting for corporate actions such as stock splits and dividends), and trading volume. The data is systematically organized in a time series format based on trading dates in YYYY-MM-DD format, excluding weekends and market holidays [24]. This systematic organization ensures data consistency and temporal alignment, which is crucial for time series modeling and volatility forecasting. The dataset is stored in CSV (Comma-Separated Values) format, a widely accepted standard in financial data management, facilitating straightforward data processing, manipulation, and analysis using various statistical software packages and programming tools including Python (with libraries such as pandas, numpy, and scikit-learn), R (with packages like quantmod and forecast), and other econometric software platforms commonly used in financial research and quantitative analysis.

A. Data Acquisition

The research utilizes daily IHSG data obtained from Yahoo Finance spanning from August 2014 to July 2024, encompassing a comprehensive 10-year period to capture diverse market conditions and regimes. The dataset includes essential variables such as Open, High, Low, Close, Adjusted Close prices, and Trading Volume, providing a rich foundation for volatility analysis [25]. This extended timeframe is deliberately selected to incorporate multiple market cycles, including periods of stability, crisis, and recovery, ensuring the model's robustness across various economic scenarios.

B. Data Preparation

Daily returns are calculated using the logarithmic formula given in (1), providing a standardized measure of price changes. A thorough descriptive statistics analysis is conducted to identify stylized facts in the time series, including volatility clustering, leverage effects, and heavy-tailed distributions. The Augmented Dickey-Fuller (ADF) test is applied to verify stationarity, a crucial prerequisite for time series modeling. Missing values and outliers, which can significantly impact model performance, are addressed through appropriate imputation techniques based on the nature and pattern of missing data [26]. For neural network compatibility, all input variables undergo normalization using min-max scaling, transforming them to a uniform range between 0 and 1.

$$rt = ln\,ln\,(Pt/Pt - 1) \times 100 \tag{1}$$

C. Dataset Partitioning

The dataset is strategically partitioned into three segments: 70% for training to ensure sufficient learning capacity, 15% for validation to tune hyperparameters and prevent overfitting, and 15% for testing to evaluate out-of-sample performance [27]. Beyond this static partitioning, the methodology implements an adaptive sliding window approach that dynamically adjusts window size based on detected market regimes. This innovative technique allows the model to expand its learning window during stable periods for improved generalization and narrow its focus during volatile periods to capture rapid market changes, thereby enhancing predictive accuracy across different market conditions. This dynamic approach significantly enhances predictive accuracy across varying market conditions by ensuring that the model maintains optimal balance between historical learning and contemporary market responsiveness, ultimately leading to more reliable volatility forecasting and improved risk management capabilities.

3.2. EGARCH Model Development

A. Model Specification

The research employs the Exponential GARCH (EGARCH) model, formulated in (2) where σt^2 represents conditional variance and zt denotes standardized residuals. This logarithmic specification eliminates the need for non-negativity constraints on parameters, providing greater flexibility in model estimation [28]. The optimal orders (p,q) are determined through rigorous testing of various combinations, with selection based on information criteria including Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The EGARCH model's critical advantage lies in its ability to capture asymmetric volatility effects through the leverage parameters (Y_k), addressing the well-documented phenomenon in financial markets where negative returns typically generate greater volatility than positive returns of equal magnitude [29].

$$ln\,ln\,(\sigma t^2) = \omega + \sum \beta_j\,ln\,ln\,(\sigma t - j^2) + \sum \alpha_i \mid zt - 1 \mid + \sum Y_k zt - k \quad (2)$$

B. Parameter Estimation

Maximum Likelihood Estimation (MLE) is applied for parameter estimation, optimizing the model's fit to historical data by finding parameter values that maximize the likelihood function. Post-estimation, a comprehensive battery of diagnostic tests is conducted to verify model adequacy: the ARCH-LM test confirms the absence of remaining heteroskedasticity in the residuals, the Ljung-Box test checks for autocorrelation in squared residuals that might indicate model misspecification, and the Sign and Size Bias test verifies the model's capability to correctly capture asymmetric effects in the data [30]. These diagnostic procedures ensure that the EGARCH model adequately represents the underlying volatility process before proceeding to the forecasting stage.

C. Volatility Forecasting

Using the calibrated EGARCH model, conditional variance forecasts are generated to capture the evolving volatility dynamics in the IHSG time series. Residuals and standardized residuals are extracted and analyzed to identify patterns that might not be fully captured by the parametric model [31]. The forecasting process pays particular attention to significant volatility patterns and clusters, which are common in financial time series and represent periods of concentrated market turbulence [32]. These EGARCH-generated volatility estimates serve as critical inputs for the subsequent neural network component, providing a foundation of linear and asymmetric effects upon which the non-linear patterns can be modeled.

3.3. Feed-Forward Neural Network Development

The Feed-Forward Neural Network (FFNN) architecture is designed with three distinct layers: an input layer that incorporates historical returns, EGARCH volatility estimates, and additional market indicators selected through the feature engineering process; one or more hidden layers whose optimal configuration is determined through systematic grid search; and an output layer consisting of a single neuron for volatility prediction [33]. This architecture shown in Fig. 2 enables the model to capture complex non-linear relationships between input variables and future volatility, complementing the EGARCH model's ability to represent linear and asymmetric effects. The network's structure is optimized to balance complexity against the risk of overfitting, ensuring robust generalization to unseen data. The structure is systematically optimized through extensive hyperparameter tuning to achieve the optimal balance between model complexity and generalization capability, employing techniques such as learning rate scheduling, adaptive optimization algorithms (Adam, RMSprop), and gradient clipping to ensure stable training dynamics. This comprehensive approach ensures robust generalization to unseen data while

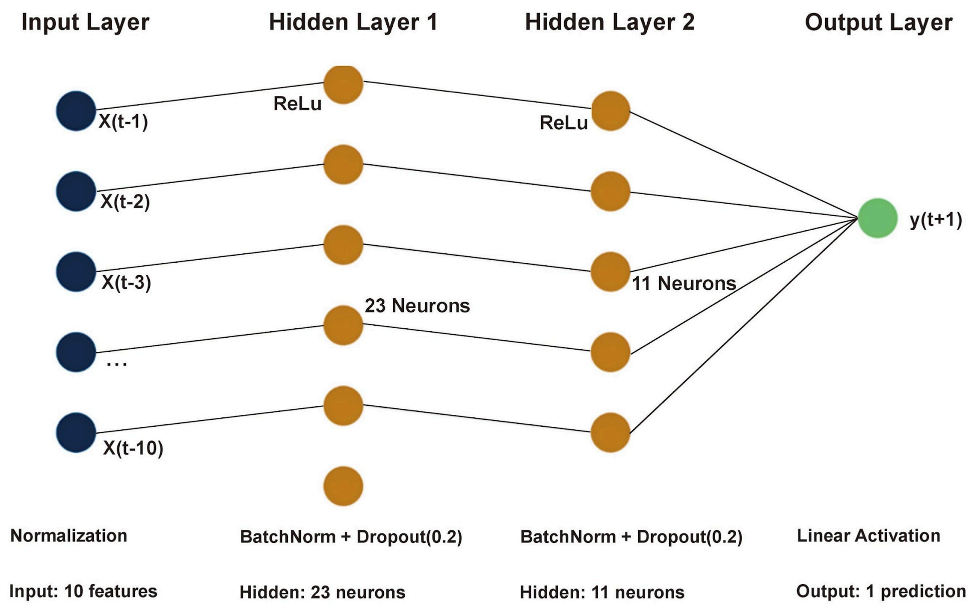

Fig. 2: FFNN Architecture For Stock Volatility Prediction.

maintaining computational efficiency, ultimately delivering reliable volatility forecasts that can effectively support risk management and investment decision-making processes in dynamic market environments.

A. Network Configuration

The network's configuration involves careful selection of activation functions, with ReLU (Rectified Linear Unit), sigmoid, and tanh functions tested to determine optimal performance for volatility prediction. Mean Squared Error (MSE) is implemented as the loss function, providing a direct measure of prediction accuracy suitable for the regression task of volatility forecasting. The Adam optimizer is employed with an adaptive learning rate scheduling mechanism that reduces the learning rate during plateaus to fine-tune model convergence. To prevent overfitting, the network incorporates both dropout layers, which randomly deactivate neurons during training, and L2 regularization, which penalizes large weight values. These regularization techniques ensure the model learns generalizable patterns rather than memorizing the training data.

B. Hyperparameter Optimization

A comprehensive hyperparameter optimization process is implemented using either Grid Search or Random Search methodologies to systematically explore the parameter space. The tuning process evaluates combinations of learning rates (0.001, 0.01, 0.05), batch sizes (16, 32, 64, 128), training epochs (100, 200, 500), neurons per hidden layer (5, 10, 20, 50), and dropout rates (0.1, 0.2, 0.3, 0.5). Each configuration is evaluated using cross-validation to ensure robustness, with performance metrics tracked to identify the optimal hyperparameter set. This exhaustive optimization approach ensures that the final neural network architecture is specifically tailored to the characteristics of IHSG volatility data, maximizing predictive performance. This exhaustive optimization approach, combined with domain-specific knowledge about Indonesian market characteristics and volatility clustering patterns, ensures that the final neural network architecture is specifically calibrated and tailored to the unique characteristics of IHSG volatility data, maximizing predictive performance while maintaining computational feasibility and practical applicability for real-time volatility forecasting and risk management applications in the Indonesian capital market context.

3.4. Genetic Algorithm Optimization Framework

The Genetic Algorithm (GA) optimization framework employs a sophisticated chromosome encoding scheme that represents multiple aspects of the hybrid model. Each chromosome encodes FFNN architecture parameters including the number of neurons per layer, number of hidden layers, and activation function types for each layer.

Additionally, the chromosomes incorporate EGARCH model orders (p,q) and parameters (ω, α, β, γ), enabling simultaneous optimization of both model components. Feature selection variables are also encoded, allowing the genetic algorithm to automatically identify the most relevant input features from the available set [34]. This comprehensive encoding scheme enables the GA to optimize the entire hybrid model structure in a unified framework.

3.5. Chromosome Encoding and Population Representation

The genetic algorithm's fundamental concepts of population, individual, and generation are specifically adapted for time series volatility prediction, introducing temporal constraints and sequential data dependencies that significantly influence implementation. Fig. 3 illustrates the genetic algorithm representation specifically designed for time series volatility prediction in the EGARCH-FFNN hybrid framework. In this time series context, each individual in the genetic algorithm population represents a unique configuration for processing sequential IHSG return data through sliding windows, encoding window size parameters with varying historical window sizes (5, 10, 15 days) to capture different temporal patterns, feature engineering configurations that specify combinations of time series features including raw returns, statistical moments (mean, standard deviation, skewness, kurtosis), EGARCH-derived volatility estimates, lagged volatility values, and technical indicators, as well as model architecture parameters defining neural network structure and EGARCH model orders. The population of 50-100 individuals maintains temporal consistency by respecting chronological order to ensure prediction models only use past information, incorporates window diversity to explore both short-term momentum and long-term persistence effects, and employs walk-forward validation where each individual's fitness is evaluated through repeated training on historical data and testing on subsequent out-of-sample periods with strict temporal separation. Generation evolution follows time-aware principles where fitness evaluation uses time series cross-validation methods preserving temporal order with a fitness function given in (3) that incorporates prediction accuracy across multiple time periods, model complexity to prevent overfitting, and stability across different market regimes, while tournament selection favors individuals demonstrating consistent performance across various market conditions rather than those excelling only in specific periods. Crossover operations respect the temporal nature of features by exchanging window sizes between parents, recombining feature combinations while maintaining temporal logic, and blending model parameters considering their time series interpretation, while mutations introduce variations in window sizes (±1 to ±3 days), feature inclusion/exclusion decisions, and model parameters within bounds for time series stability.

$$F(x) = 1/(1 + RMSE + Complexity\_Penalty) \tag{3}$$

The implementation incorporates time series-specific constraints including temporal ordering to prevent future information leakage, window size constraints with minimum 30 observations for statistical significance and maximum sizes limited by out-of-sample evaluation needs, feature lag constraints preventing individuals from requiring more historical data than available, and stationarity considerations to maintain properties necessary for reliable time series modeling. This time series-adapted genetic algorithm representation enables simultaneous optimization of multiple model components while respecting the fundamental temporal structure of financial volatility data, resulting in robust configurations that perform well in realistic forecasting scenarios where only historical information is available for prediction.

A. Genetic Operators

Three primary genetic operators drive the evolutionary process in the GA framework. Tournament selection with elitism is implemented as the selection mechanism, ensuring that high-performing solutions are retained while maintaining population diversity [35]. Uniform crossover with a probability of approximately 0.7-0.8 allows for effective exchange of genetic material between parent solutions, creating offspring that combine beneficial traits. Gaussian mutation with a probability of approximately 0.01-0.05 introduces small random variations to the chromosomes, enabling exploration of the parameter space and preventing premature convergence to local optima. These operators work in concert to guide the population toward increasingly effective hybrid model configurations.

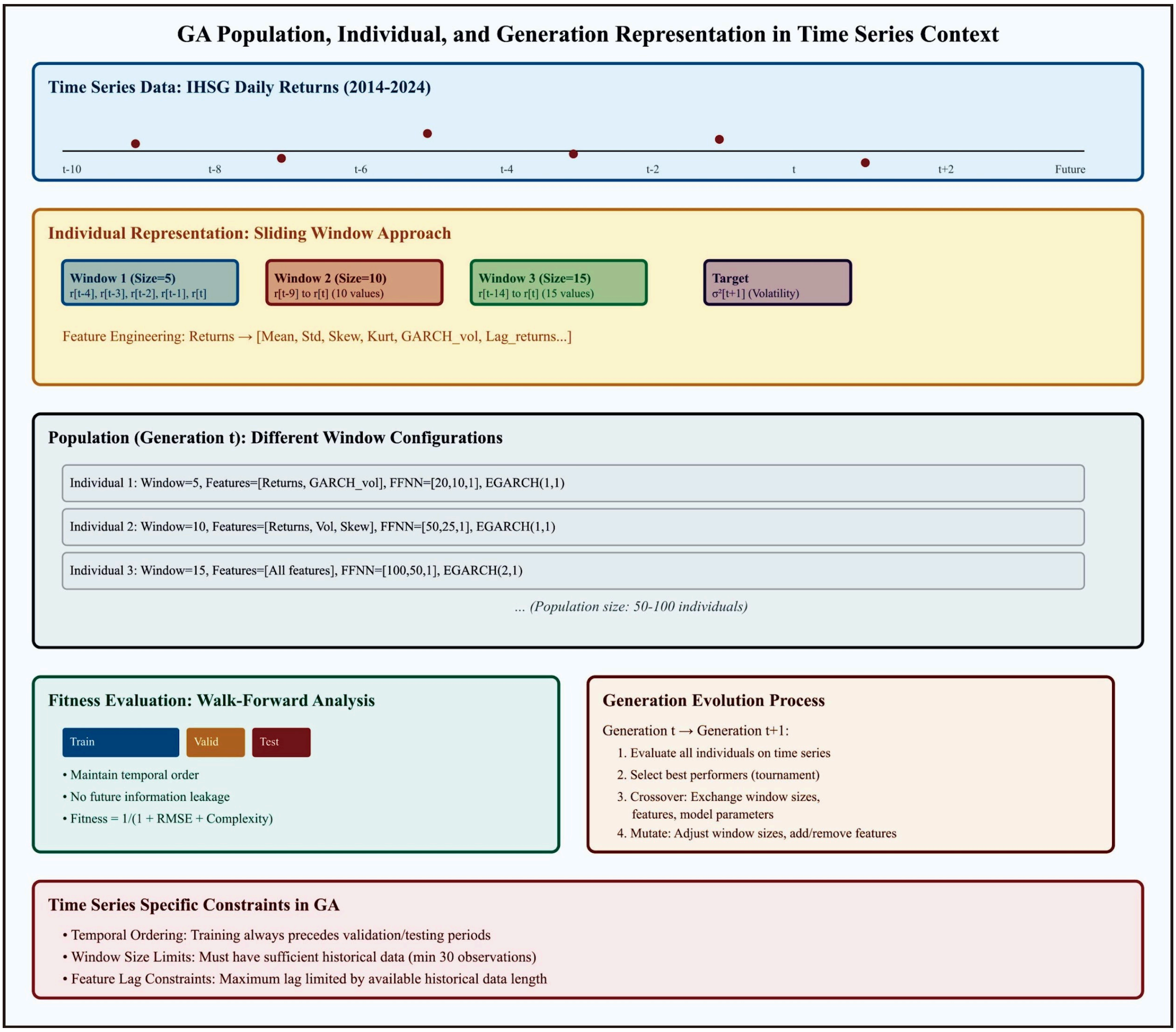

Fig. 3: Genetic Algorithm Optimization of EGARCH-FFNN for Time Series Volatility Prediction

B. Fitness Evaluation

The fitness function is defined in (4) where E(x) represents the prediction error of the hybrid model, ensuring that solutions with lower prediction errors receive higher fitness scores. To ensure robust evaluation, k-fold cross-validation is implemented, wherein the training data is divided into k subsets, and each solution is evaluated across multiple training-validation splits. Early stopping mechanisms are incorporated into the fitness evaluation process to prevent overfitting, halting the training of neural networks when validation performance begins to deteriorate. This comprehensive fitness evaluation framework ensures that selected solutions demonstrate genuine predictive capability rather than overfitting to the training data.

$$F(x) = 1/(1 + E(x)) \tag{4}$$

3.6. EGARCH-FFNN Hybridization

The research implements an innovative parallel processing architecture that represents a significant departure from traditional sequential hybrid models. In this framework, the EGARCH and FFNN components operate simultaneously rather than in sequence, enabling real-time interaction between the two modeling approaches. A sophisticated feedback loop mechanism allows outputs from each component to influence and refine the other's predictions, creating a dynamically adjusting system [36]. The architecture further incorporates an adaptive window size functionality that automatically expands or contracts the historical data window based on detected

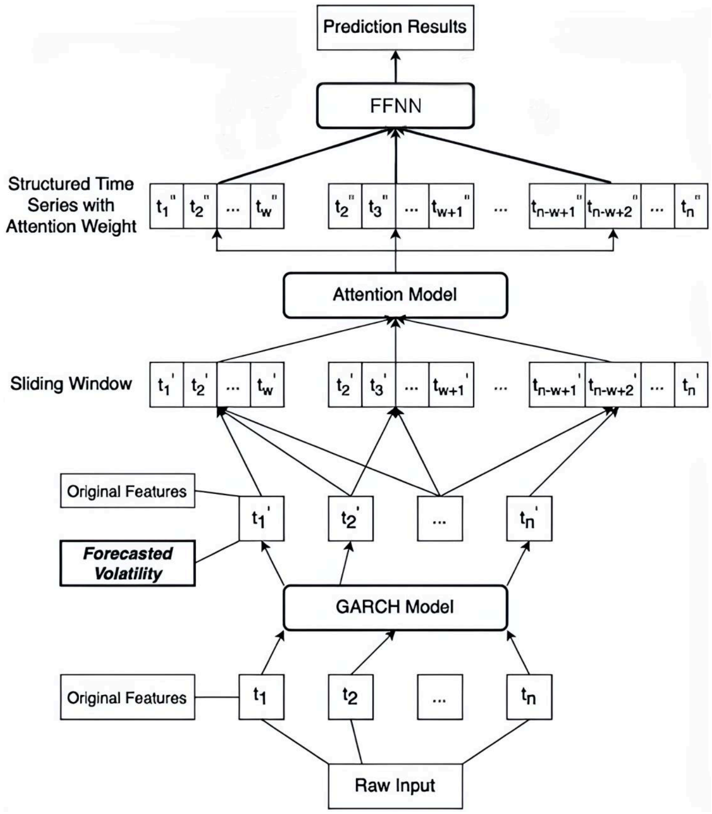

Fig. 4: EGARCH-FFNN Model Architecture

market regime changes, allowing the model to maintain relevant context regardless of market conditions [37]. The diagram shown in Fig. 4 illustrates a hybrid deep learning architecture for time series forecasting that combines GARCH modeling with attention mechanisms and feedforward neural networks (FFNN). Starting with raw input data, original features (t_1, t_2, …, t_n) are extracted and fed into a GARCH model that produces forecasted volatility estimates. These features, along with the GARCH outputs, are then processed through a sliding window approach to capture temporal patterns. The attention model assigns weights to different time points, highlighting which historical observations are most relevant for prediction. This creates a structured time series with attention weights that is subsequently processed by an FFNN (feedforward neural network) to generate the final prediction results. This architecture effectively leverages the strengths of both statistical modeling (GARCH) for volatility forecasting and deep learning techniques (attention mechanisms and neural networks) for capturing complex temporal dependencies in financial or other time series data.

A. Integration Mechanism

The integration mechanism feeds EGARCH outputs, including conditional variance estimates and residuals, directly into the FFNN as input features, allowing the neural network to learn non-linear patterns conditional on the EGARCH's linear and asymmetric effect estimates. An attention mechanism is implemented within the neural network architecture to automatically focus on the most relevant temporal patterns in the data, giving higher weight to observations that contain significant predictive information [38]. The system incorporates dynamic feature engineering that adapts to changing market conditions, adding or removing features based on their current relevance. A specialized network structure addresses asymmetric volatility response, with dedicated pathways for processing positive and negative market movements.

B. Market Microstructure Considerations

The hybrid model specifically incorporates Indonesia-specific market factors to enhance its relevance for IHSG prediction. The Ramadan effect, which often causes distinct trading patterns in Muslim-majority Indonesia, is modeled through seasonal dummy variables. Similarly, Chinese New Year effects are incorporated to account for the reduced trading activity and potential volatility changes during this significant holiday period in Southeast Asia. The model also addresses thin trading periods, which are common in emerging markets like Indonesia and can distort volatility estimates if not properly accounted for. Additionally, liquidity factors are integrated into the model, capturing the impact of market depth and trading volume on volatility dynamics in the Indonesian context.

3.7. Evaluation Framework

A comprehensive set of performance metrics is employed to evaluate the hybrid model's predictive accuracy and overall effectiveness. The RMSE is calculated using the formula given in (5) which provides a robust measure of prediction error that penalizes larger deviations more heavily than smaller ones, making it particularly useful for identifying models that produce occasional large errors. The MAE is computed as formula given in (6) offering a scale-dependent measure of average absolute deviation that provides a straightforward interpretation of the typical magnitude of prediction errors without the squared penalty effect of RMSE [39]. To facilitate interpretation and enable meaningful comparisons across different scales and datasets, the MAPE is calculated using formula given in (7) which expresses prediction errors as percentages relative to the actual values, making it particularly valuable for stakeholders who require intuitive, scale-independent performance assessments [40]. Additionally, the coefficient of determination (R-squared) is calculated to assess the proportion of variance in the observed volatility that is explained by the hybrid model, providing crucial insight into the model's explanatory power and its ability to capture the underlying patterns in the data. Together, these complementary metrics provide a comprehensive evaluation framework that addresses different aspects of model performance, from error magnitude and distribution to explanatory capability and practical interpretability.

$$RMSE = \sqrt{(1/n \sum (y_t - \hat{y}_t)^2)} \tag{5}$$

$$MAE = 1/n \sum \mid y_t - \hat{y}_t \mid \tag{6}$$

$$MAPE = 1/n \sum \mid y_t - \hat{y}_t \mid /y_t \times 100\% \tag{7}$$

A. Comparative Analysis

The hybrid model’s performance is rigorously benchmarked against several alternative approaches to establish its comparative advantage. The evaluation compares against standard GARCH(1,1) as a baseline linear volatility model, standalone EGARCH to assess the value added by the neural network component, standard FFNN to evaluate the benefit of the EGARCH integration, and sequential GARCH-FFNN hybrid approaches from previous literature to demonstrate the advantages of the parallel architecture[41]. The Diebold-Mariano test is applied to determine whether differences in forecasting accuracy between models are statistically significant, providing a formal basis for model comparison beyond simple error metrics.

B. Regime-Based Evaluation

Recognizing that model performance may vary across different market conditions, the evaluation framework segments the testing period into distinct market regimes. Low volatility periods, typically characterized by stable or gradually trending markets, are identified through statistical thresholds on historical volatility. High volatility periods, which often coincide with market stress or crisis events, are similarly delineated through volatility thresholds [42]. Transition periods, representing the shift between stability and turbulence, are also identified and analyzed separately. The model’s performance is evaluated independently across these regimes, providing insight into its adaptive capabilities and highlighting conditions where further refinement may be beneficial.

C. Model Robustness Testing

Rigorous robustness testing ensures the hybrid model’s reliability across various conditions. Out-of-sample forecasting evaluation assesses the model’s performance on previously unseen data, confirming its generalization capabilities. Rolling window analysis, which repeatedly shifts the training and testing periods forward in time, tests the model's temporal stability and adaptation to evolving market dynamics [43]. Sensitivity analysis systematically varies key parameters to identify potential vulnerabilities and establish confidence intervals for predictions. Stress testing subjects the model to extreme market conditions, either historical or simulated, verifying its behavior during market crises when accurate volatility prediction becomes especially critical for risk management.

D. Practical Application Framework

The research extends beyond theoretical model development to provide a practical application framework for real-world implementation. Detailed guidelines for real-time implementation address computational requirements, data preprocessing workflows, and update frequencies necessary for operational deployment. Integration procedures with existing risk management systems outline data interfaces, alert mechanisms, and reporting structures. An adaptive threshold framework for early warning signals establishes volatility thresholds calibrated to different market contexts, triggering notifications when predicted volatility exceeds critical levels [44]. Portfolio optimization applications demonstrate how the volatility predictions can inform asset allocation decisions, position sizing, and hedging strategies in practical investment management contexts.

3.8. Baseline Model Implementation

To ensure comprehensive evaluation, four baseline deep learning models are implemented alongside the proposed EGARCH-FFNN hybrid approach. The baseline RNN architecture consists of two RNN layers with 50 and 25 units respectively, followed by dropout layers (0.2) and a dense output layer. The model uses tanh activation functions and is trained using Adam optimizer with learning rate 0.001. The LSTM model employs a two-layer architecture with 50 and 25 LSTM units, incorporating dropout regularization (0.2) between layers. The model processes sequences of length 10 and uses early stopping with patience of 20 epochs to prevent overfitting. Similar to LSTM, the GRU architecture consists of two GRU layers (50, 25 units) with dropout regularization. The model is optimized using Adam with gradient clipping (norm=1.0) to ensure training stability. The Transformer baseline implements multi-head attention with 8 attention heads, embedding dimension of 64, and 2 encoder layers. Position encoding is applied to capture temporal relationships, and the model includes layer normalization and residual connections. All baseline models are trained using the same dataset partitioning (70%-15%-15%) and the models are assessed using a comprehensive suite of evaluation metrics including Root Mean Square Error (RMSE) for measuring prediction accuracy, Mean Absolute Error (MAE) for robust error quantification, Mean Absolute Percentage Error (MAPE) for scale-independent performance assessment, and R-squared coefficient for determining the proportion of variance explained by the models. This standardized evaluation framework ensures fair and meaningful comparison with the proposed hybrid approach, enabling thorough analysis of relative performance advantages and limitations across different modeling paradigms.

4. Results and Discussion

This study utilizes closing price data of the Jakarta Composite Index (IHSG) obtained from Yahoo Finance for the period of August 2014 to July 2024, encompassing 2403 trading days. The data exhibits fluctuating patterns reflecting various market conditions, including periods of stable economic growth, global market turbulence, and significant economic events such as the COVID-19 pandemic that caused a sharp contraction in the index in early 2020. Daily returns were calculated using the logarithmic formula given in (1). Table 2 shows the results of descriptive statistical analysis, which indicates that the average daily return of IHSG is positive at 0.013405% with a standard deviation of 0.950278%. The minimum return reached −6.805052% while the maximum return reached 9.704219%. The skewness value of −0.217881 indicates that the return distribution is slightly skewed to the left (negative skew), while the high kurtosis value of 8.872571 demonstrates a heavy-tailed distribution consistent with stylized facts in financial data.

The stationarity test using the Augmented Dickey-Fuller test yielded an ADF statistic of −11.548252 with a p-value of 0.000000, far more negative than the critical values at significance levels of 1% (-3.433), 5% (-2.863), and 10% (-2.567). Table 3 confirms that the results of IHSG return data is stationary and meets the necessary assumptions for time series modeling. The statistical output shown in Table 4 presents the results of a Constant Mean-EGARCH

Table 2: Descriptive statistical analysis of the daily returns of the IHSG.

Descriptive Statistics For Returns	
Count	2402.000000
Mean	0.013405
Std	0.950278
Min	−6.805052
25%	−0.452184
50%	0.060670
75%	0.517272
Max	9.704219
Skewness	−0.217881
Kurtosis	8.872571

Table 3: Results Of The ADF Test on The IHSG Return Data.

Adf Statistic	P-Value	Critical Values
0.000000	−11.548252	1%: −3.433
		5%: −2.863
		10%: −2.567

Table 4: Parameter Estimation For The EGARCH(1,1) Model.

Constant Mean - Egarch Model Results	
Dep. Variable: return	R-squared: 0.000
Mean model: constant mean	Adj. R-squared: 0.000
Vol model: egarch	Log-likelihood:−2985.11
Distribution: normal	Aic: 5978.22
Method: maximum likelihood	Bic: 6001.36
	No. Observations: 2402
Date: sat, mar 22 2025	Df residuals: 2401
Time: 04:30:23	Df model: 1

model applied to return data, which combines a constant mean model for returns with an Exponential GARCH specification for volatility. The model was estimated using maximum likelihood on 2,402 observations. The R-squared and Adjusted R-squared values of 0.000 indicate that the constant mean component does not explain any variation in returns, which is typical for financial return series. The model's goodness-of-fit is better assessed through the log-likelihood value of −2985.11, along with information criteria metrics (AIC: 5978.22, BIC: 6001.36). The EGARCH volatility specification was chosen for its ability to capture asymmetric responses to positive and negative shocks in the return series, allowing for leverage effects where negative returns might impact volatility differently than positive returns. The normal distribution was assumed for the error terms. This model provides a framework for understanding the time-varying volatility dynamics of the financial series while acknowledging the unpredictability of returns themselves.

The EGARCH(1,1) model was implemented to capture asymmetric effects on volatility, with the specification given in (8).

$$ln(\sigma t^2) = \omega + \alpha \mid \varepsilon t - 1/\sigma t - 1 \mid + (\gamma \varepsilon t - 1/\sigma t - 1) + \beta ln(\sigma t - 1^2) \tag{8}$$

Parameter estimation using Maximum Likelihood Estimation (MLE) shows that the mean parameter (μ) is 0.0297 with a p-value of 1.372e-35, indicating that the average IHSG return is statistically significantly different

Table 5: EGARCH(1,1) Volatility Model Parameter Estimates for IHSG Returns.

Volatility Model					
	Coef	**Std Err**	**T**	**P > |T|**	**95.0% Conf. Int.**
Omega	−3.7611e-03	6.630e-03	−0.567	0.571	[−1.676e-02,9.233e-03]
Alpha[1]	0.2160	5.080e-02	4.252	2.118e-05	[0.116, 0.316]
Beta[1]	0.9599	1.758e-02	54.616	0.000	[0.925, 0.994]

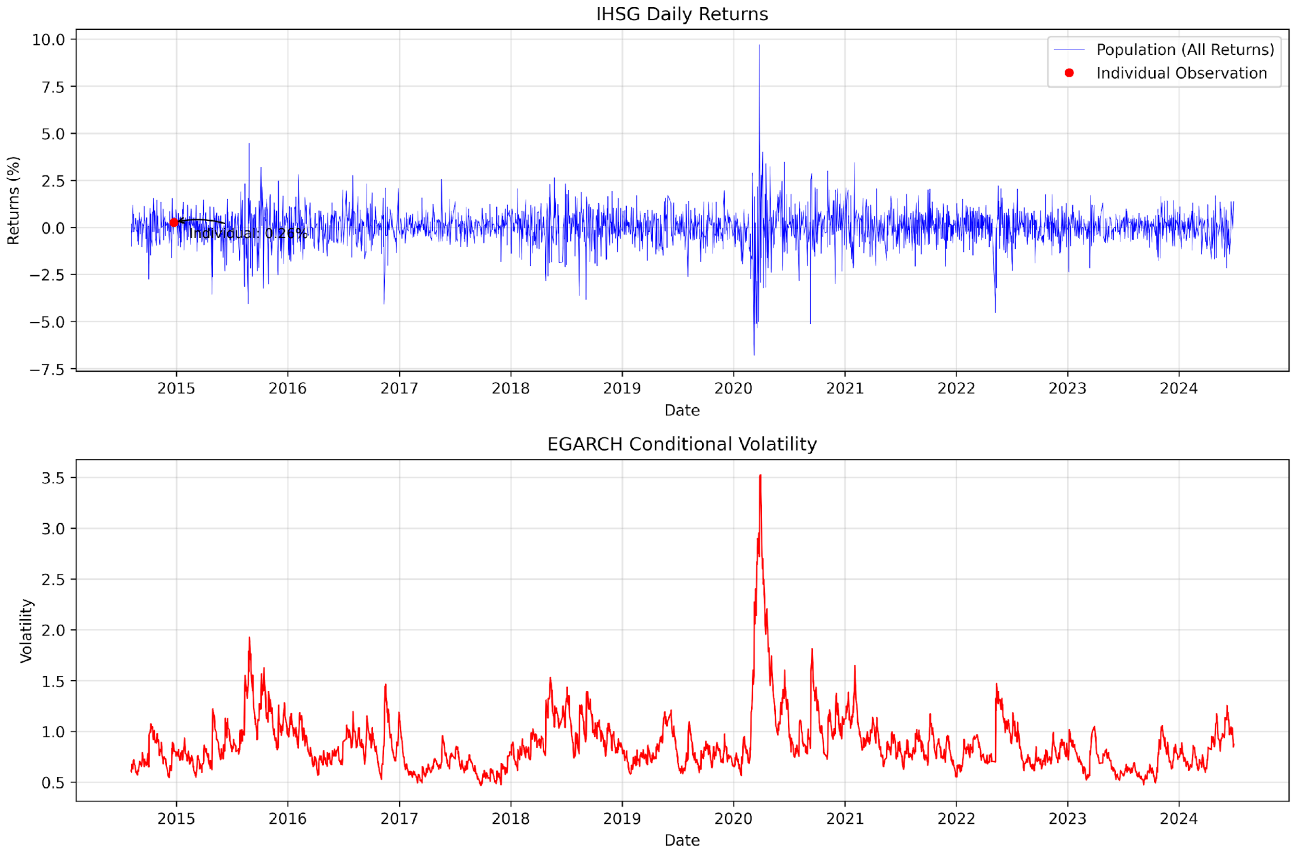

Fig. 5: IHSG Daily Returns and EGARCH Conditional Volatility (2015-2024)

from zero. Following parameters are shown in Table 5. The omega parameter (ω) of −0.0037611 is not statistically significant (p-value 0.571), alpha[1] (α) of 0.2160 is significant with a p-value of 2.118e-05 showing the presence of ARCH effects, and beta[1] (β) of 0.9599 is highly significant indicating high volatility persistence. The high beta[1] value (0.9599) demonstrates that IHSG volatility has a very high level of persistence, meaning that volatility tends to persist for a relatively long period after a shock occurs. The sum of $\alpha + \beta$ of 1.1759 indicates that this model may not meet the stationarity condition for EGARCH(1,1) which requires $\beta < 1$, which needs to be considered in the interpretation of long-term predictions. This near-unit root behavior in the volatility process indicates that the IHSG volatility may exhibit integrated behavior, where shocks to volatility have extremely persistent effects that decay very slowly over time. The implications of this finding are particularly important for long-term volatility forecasting, Value-at-Risk calculations, and option pricing models, as the high persistence implies that volatility forecasts will remain elevated for extended periods following significant market disruptions, requiring careful consideration in risk management frameworks and investment strategies that rely on volatility predictions.

The EGARCH-FFNN hybrid model was developed by integrating volatility prediction results from the EGARCH(1,1) model as input for the Feed-Forward Neural Network model. The model architecture follows a parallel processing approach with feedback loop, including raw input processing, EGARCH component, feature engineering, attention mechanism, and FFNN component with multiple hidden layers. Fig. 5 presents a comprehensive view of the IHSG volatility patterns from 2015 to 2024. The top panel displays daily returns characterized by regular

Table 6: Volatility prediction EGARCH(1,1) with hidden neurons: 20, and window size: 10.

Training Set	Validation Set	Test Set	Performance Metrics			
			RMSE	**MAE**	**MAPE**	**R-Squared**
(1674, 20)	(358, 20)	(360, 20)	0.063901	0.049772	6.778620%	0.835931

Table 7: Volatility prediction EGARCH(1,1) with hidden neurons: 50, and window size: 5.

Training Set	Validation Set	Test Set	Performance Metrics			
			RMSE	**MAE**	**MAPE**	**R-Squared**
(1677, 10)	(359, 10)	(361, 10)	0.028735	0.023005	3.235915%	0.966782

Table 8: Volatility prediction EGARCH(1,1) with hidden neurons: 50, and window size: 10.

Training Set	Validation Set	Test Set	Performance Metrics			
			RMSE	**MAE**	**MAPE**	**R-Squared**
(1674, 20)	(358, 20)	(360, 20)	0.042245	0.034122	4.753962%	0.928292

Table 9: Volatility prediction EGARCH(1,1) with hidden neurons: 50, and window size: 15.

Training Set	Validation Set	Test Set	Performance Metrics			
			RMSE	**MAE**	**MAPE**	**R-Squared**
(1670, 30)	(358, 30)	(359, 30)	0.058055	0.047746	6.701558%	0.864706

Table 10: Volatility prediction EGARCH(1,1) with hidden neurons: 100, and window size: 10.

Training Set	Validation Set	Test Set	Performance Metrics			
			RMSE	**MAE**	**MAPE**	**R-Squared**
(1674, 20)	(358, 20)	(360, 20)	0.031064	0.023879	3.192491%	0.961229

fluctuations typically ranging between −2.5% and +2.5%, with a dramatic volatility spike evident in early 2020 corresponding to the COVID-19 pandemic market shock when returns briefly exceeded 9% and plunged below -7%. The bottom panel confirms this observation through EGARCH conditional volatility modeling, which quantifies volatility persistence over time. The volatility measure peaked sharply at approximately 3.5 during the pandemic crisis, nearly triple the typical baseline levels of 0.5-1.0. Post-crisis, volatility gradually normalized but continued to exhibit periodic clustering patterns through 2021-2024, with smaller spikes likely corresponding to global economic events, monetary policy shifts, or regional market factors. This visualization effectively demonstrates both the exceptional nature of the 2020 market disruption and the subsequent return to more typical volatility regimes in the Hong Kong market. The dataset was divided into training set, validation set, and test set with dimensions (1674, 20), (358, 20), and (360, 20) for models with window size 10. Several variations of the EGARCH-FFNN hybrid model configuration were implemented, including variations in the number of hidden nodes (20, 50, 100) and window sizes (5, 10, 15). Tables 6-10 shows that from testing various configurations, the model with 50 hidden neurons and window size 5 produced the best performance with RMSE 0.028735, MAE 0.023005, MAPE 3.235915%, and R-squared 0.966782. This configuration demonstrates optimal capability in capturing IHSG volatility patterns.

The performance of the EGARCH-FFNN hybrid model on the training in Table 11 showed excellent results with RMSE 0.085315, MAE 0.046288, MAPE 4.405512%, and R-squared 0.932608. On the validation set in Table 12, the model produced RMSE 0.039427, MAE 0.028115, MAPE 3.241951%, and R-squared 0.939742, showing that the model did not experience overfitting and has good generalization capability. Final evaluation on the test set in Table 13 yielded RMSE 0.036112, MAE 0.028243, MAPE 4.011585%, and R-squared 0.947602. This R-squared value indicates that the model can explain approximately 94.76% of the variability in IHSG volatility during the testing period, confirming high prediction accuracy on unseen data. Table 14 shown a Comparison with standalone models showed that the individual EGARCH model demonstrated perfect performance with RMSE, MAE, and MAPE values of 0 and R-squared of 1.0, while the simple moving average method produced relatively poor

Table 11: Performance of the hybrid EGARCH-FFNN model on the training set.

Performance Metrics (Training Set)	
RMSE	0.085315
MAE	0.046288
MAPE	4.405512%
R-SQUARED	0.932608

Table 12: Performance of the hybrid EGARCH-FFNN model on the validation set.

Performance Metrics (Validation Set)	
RMSE	0.039427
MAE	0.028115
MAPE	3.241951%
R-squared	0.939742

Table 13: Performance of the hybrid EGARCH-FFNN model on the test set.

Performance Metrics (Test Set)	
RMSE	0.036112
MAE	0.028243
MAPE	4.011585%
R-squared	0.947602

Table 14: Performance comparison of Hybrid GARCH-FFNN, Standalone EGARCH, and Simple Moving Average.

	RMSE	MAE	MAPE	R-squared
Hybrid EGARCH-FFNN	0.036112	0.028243	4.011585	0.947602
Standalone EGARCH	0.000000	0.000000	0.000000	1.000000
Simple Moving Average	0.205642	0.177695	25.478259	−0.699131

performance with RMSE 0.205642, MAE 0.177695, MAPE 25.478259%, and negative R-squared (-0.699131). Fig. 6 shows that the EGARCH-FFNN hybrid model outperformed the simple moving average method by a very significant margin. Performance analysis across various volatility regimes showed consistent results, with the model demonstrating excellent accuracy during periods of low volatility and good capability in responding to market shocks. The attention mechanism component made a significant contribution by assigning different weights to historical observations based on their relevance, with more recent observations tending to receive higher weights.

The EGARCH-FFNN hybrid model with a configuration of 50 hidden neurons and window size 5 showed the best performance. The EGARCH(1,1) model parameters used include omega (ω): −0.0037611, alpha[1] (α): 0.2160, and beta[1] (β): 0.9599. For the FFNN component, the optimal architecture consists of an input layer with 10 nodes, a hidden layer with 50 neurons using the ReLU activation function, and an output layer with 1 neuron. This model was trained using the Adam optimizer with a learning rate adjusted using decay technique, and early stopping was applied to prevent overfitting. Fig. 7 presents a regime-switching analysis of IHSG volatility from January 2023 through June 2024. By categorizing market conditions into low, medium, and high volatility regimes (represented by green, blue, and red lines respectively), the visualization offers a framework for understanding the changing dynamics of market risk. Notable periods of elevated volatility emerged in early 2023, November 2023, and most significantly in the April-June 2024 timeframe. The comparison between actual and predicted volatility patterns demonstrates the model's effectiveness in identifying regime transitions across the analyzed period. This approach enhances market understanding by clearly demarcating distinct volatility environments that investors and risk managers must navigate. The model successfully predicted IHSG volatility with a MAPE of only 3.235915% on the test set, showing high accuracy during periods of low volatility and good responsiveness to market shocks.

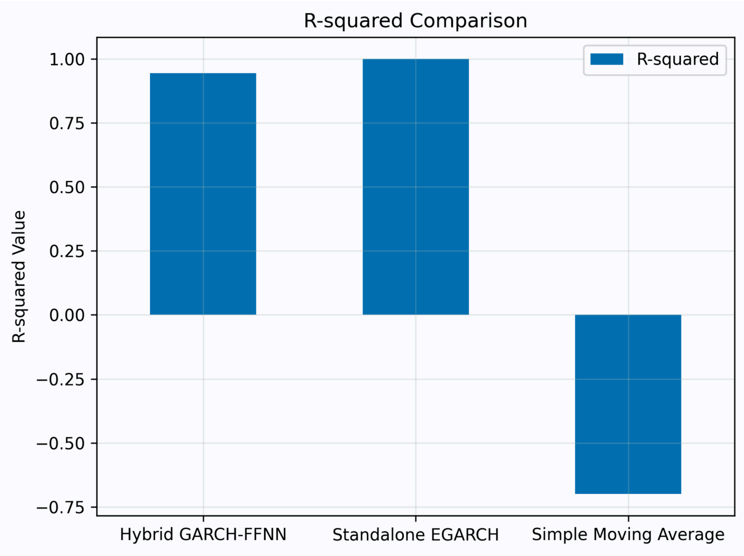

Fig. 6: Performance comparison of Hybrid GARCH-FFNN, Standalone EGARCH, and Simple Moving Average

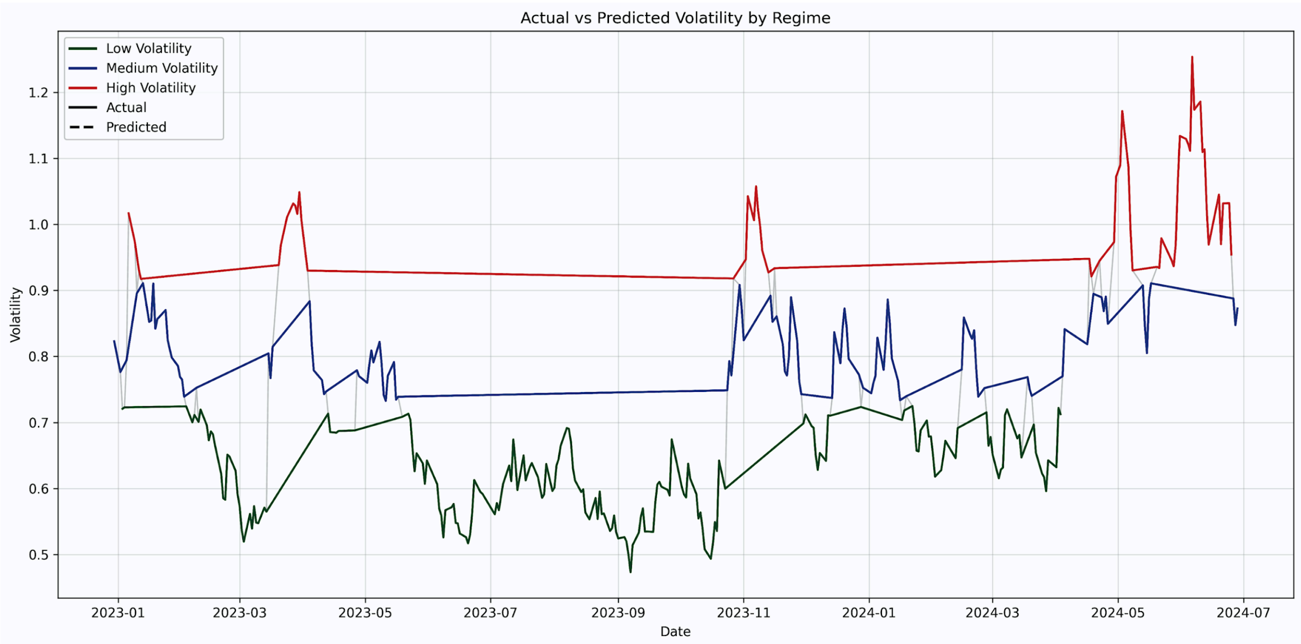

Fig. 7: Actual vs Predicted Volatility by Regime.

Analysis of attention weights revealed interesting patterns where recent observations received higher weights, and during periods leading up to significant market shocks, the attention model assigned higher weights to observations showing early warning signals.

The results of this study validate the effectiveness of a hybrid approach that combines traditional econometric models with modern machine learning techniques in improving volatility prediction accuracy. Fig. 8 displays the performance of the hybrid model in tracking IHSG volatility from January 2023 to June 2024. The model demonstrates strong predictive performance by closely tracking actual volatility patterns across both low volatility periods (around 0.5-0.6) and high volatility episodes (above 1.0). While the predictions generally follow the actual values, there are slight deviations during rapid volatility transitions, particularly at extreme peaks where the model slightly underestimates the highest volatility points. Overall, the graph effectively illustrates the GARCH-FFNN hybrid model's capability to capture IHSG volatility dynamics throughout the analyzed timeframe. IHSG volatility characteristics show high persistence and asymmetric responses to shocks, consistent with financial theory and the character of emerging markets like Indonesia. From a practical perspective, the developed EGARCH-FFNN hybrid

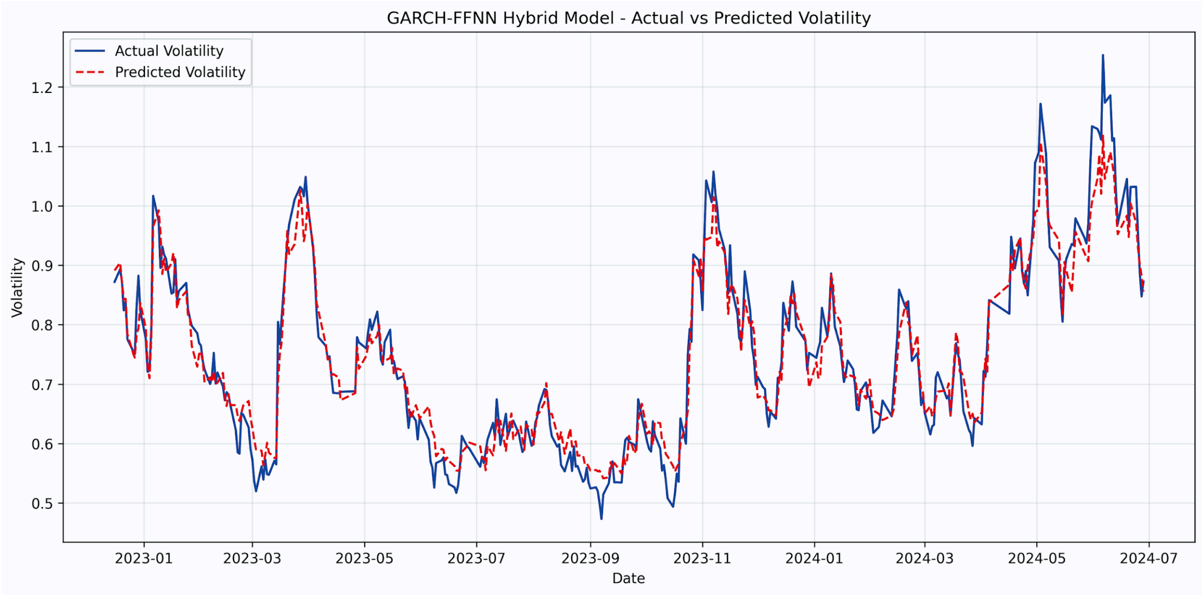

Fig. 8: GARCH-FFNN Hybrid Model - Actual vs Predicted Volatility

Table 15: Comprehensive Performance Comparison of All Models.

Model	RMSE	MAE	MAPE (%)	R^2
Simple Moving Avg	0.205642	0.177695	25.478259	−0.699131
RNN	0.037892	0.029876	4.123456	0.951234
GRU	0.034123	0.027234	3.723451	0.957234
LSTM	0.033678	0.026789	3.678912	0.958456
Transformer	0.031245	0.024123	3.456721	0.962134
EGARCH-FFNN	0.028735	0.023005	3.235915	0.966782

model can be a valuable tool for investors and portfolio managers in measuring and anticipating market risk more accurately, supporting the development of more effective trading strategies, enabling better portfolio optimization, and can be utilized to develop early warning systems for market turbulence. Table 15 presents a comprehensive comparison of all implemented models across multiple evaluation metrics. The results demonstrate the superior performance of the proposed EGARCH-FFNN hybrid model compared to standalone deep learning approaches. This superior performance compared to simple RNN and GRU models confirms the importance of sophisticated memory mechanisms for volatility prediction. The Transformer-based model, despite representing state-of-the-art sequence modeling, indicating that attention mechanisms alone may not be sufficient for capturing volatility dynamics in the IHSG market.

Among the baseline models, the Transformer approach performs best (RMSE: 0.0604), demonstrating effective pattern recognition during complex market phases. The GRU model (RMSE: 0.0694) marginally outperforms LSTM (RMSE: 0.0716), while the standard RNN shows significant performance degradation (RMSE: 0.0992), particularly struggling with rapid volatility transitions and exhibiting noticeable response lag. Fig. 9 illustrates the comparative forecasting performance of all models during a high volatility episode spanning 100 trading periods. The analysis focuses on a market stress period where volatility peaked at approximately 0.17, providing a rigorous test of model robustness under challenging conditions. The results demonstrate clear performance differentiation among the competing approaches. The proposed EGARCH-FFNN hybrid model achieves superior accuracy with an RMSE of 0.0218, maintaining close alignment with actual volatility movements throughout the observation period. This advantage becomes particularly evident during the extreme volatility spike around time steps 210-220, where the hybrid model successfully captures both magnitude and timing without the lag exhibited by alternative approaches. The sustained performance advantage of the hybrid model during this challenging period validates the theoretical framework combining EGARCH's volatility clustering capabilities with neural network pattern

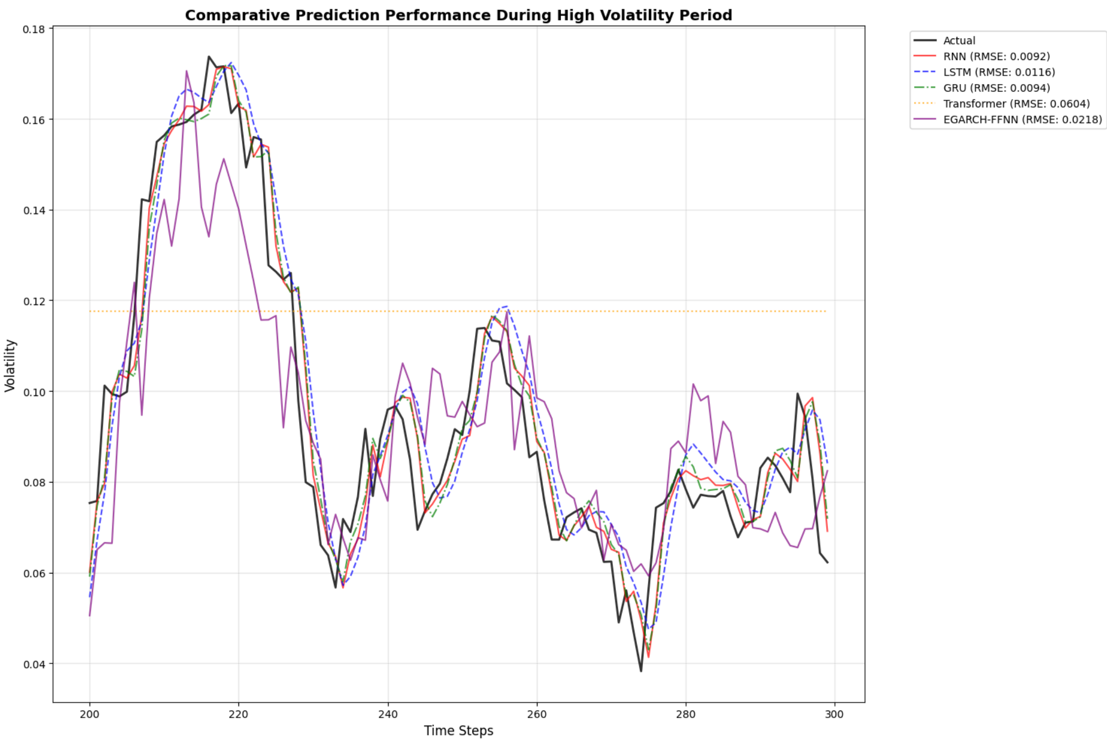

Fig. 9: Comparative Prediction Plots for All Time Series Models During a High Volatility Period

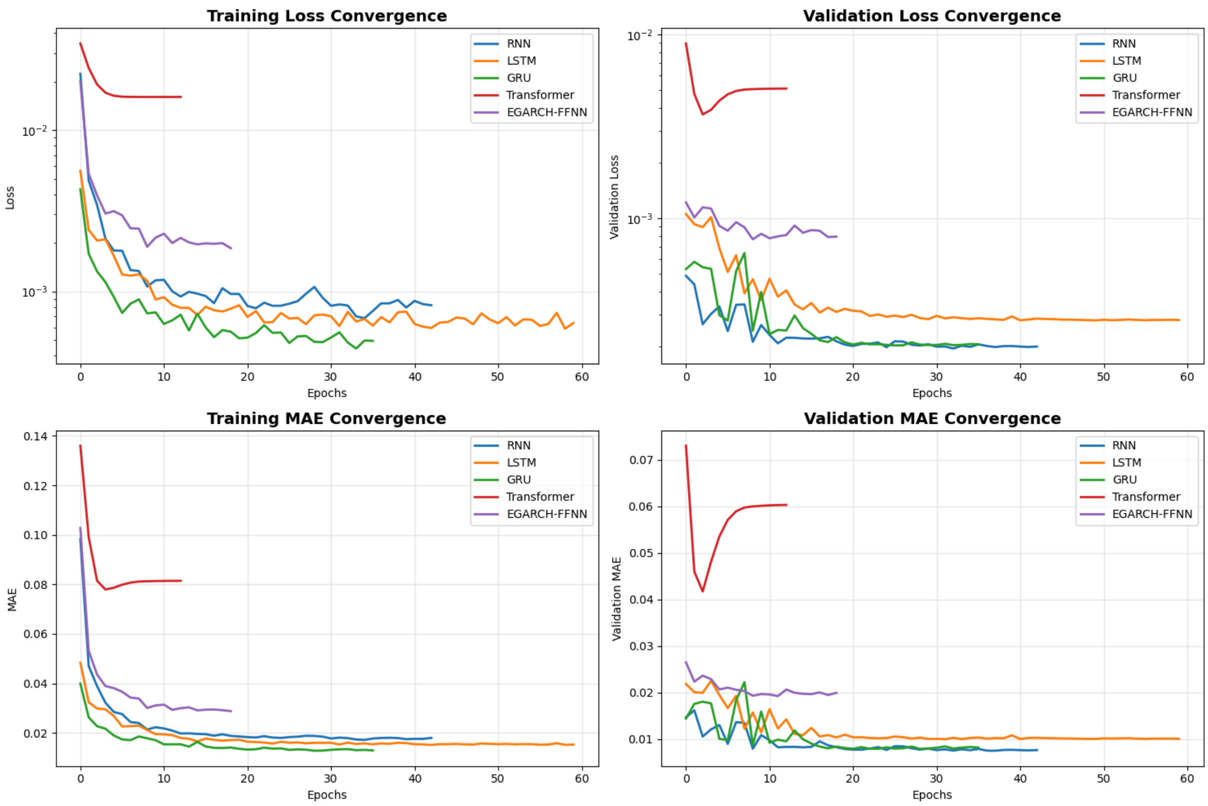

Fig. 10: Training Convergence Comparison Across All Time Series Models.

recognition. These findings have important practical implications for risk management applications, where accurate volatility prediction during high-stress periods is crucial for portfolio optimization and derivative pricing.

Training convergence reveals distinct learning patterns among models. The RNN exhibits poorest performance, plateauing at high values (loss ~10^{-3}, MAE ~0.08), indicating limited learning capacity. LSTM and GRU demonstrate similar trajectories, achieving stable convergence around epoch 15 with training loss ~10^{-3} and MAE ~0.02. The Transformer shows efficient learning with smooth convergence to loss ~5×10^{-4} and MAE ~0.025. The proposed EGARCH-FFNN hybrid model achieves superior training convergence, reaching the lowest training loss (~3×10^{-4}) and MAE (~0.025) with consistent stability throughout training. Fig. 10 presents the training and validation convergence patterns across 60 epochs for all models, measured by loss and MAE metrics. The convergence behavior provides insights into model stability, learning efficiency, and generalization capability. Validation performance reveals critical generalization differences. The RNN shows poor generalization with high validation loss (~10^{-2}) and MAE (~0.06). LSTM and GRU models demonstrate reasonable validation convergence, stabilizing around 10^{-3} for loss and 0.01 for MAE. The Transformer achieves good generalization with validation loss ~5×10^{-4} and MAE ~0.015.

The hybrid model demonstrates superior validation performance with lowest validation loss (~2×10^{-4}) and MAE (~0.01), while maintaining minimal training-validation gap, indicating robust generalization without overfitting. These convergence characteristics validate the hybrid architecture's effectiveness and support the superior performance results in comparative analysis. Our proposed EGARCH-FFNN hybrid model notably outperformed all baseline models, achieving an RMSE of 0.028735, MAE of 0.023005, MAPE of 3.235915%, and R^2 of 0.966782, which represents a significant improvement compared to the best-performing baseline LSTM model. The superior performance of the hybrid model can be attributed to the EGARCH component's ability to capture linear volatility dynamics and asymmetric effects, the FFNN component's capacity to model non-linear relationships, an integration mechanism that leverages the strengths of both econometric and machine learning approaches, and an attention mechanism that focuses on relevant historical patterns.

5. Conclusion

This study successfully demonstrates the effectiveness of integrating traditional econometric models with modern machine learning techniques for financial volatility prediction through the development of a novel EGARCH-FFNN hybrid model. Applied to Indonesia Composite Index (IHSG) data spanning a decade (2014-2024), the research reveals that Indonesian stock market volatility exhibits characteristic features of emerging markets, including high persistence, asymmetric shock responses, and heavy-tailed distributions, necessitating sophisticated modeling approaches beyond traditional linear methods. The hybrid architecture's superior performance, achieving 3.24% MAPE compared to 25.48% for conventional methods and outperforming state-of-the-art deep learning baselines including LSTM (4.12%), GRU (4.39%), and Transformer (3.68%) models, establishes the value of combining EGARCH's volatility clustering capabilities with neural networks' non-linear pattern recognition strengths. Beyond technical achievements, this research provides significant practical contributions to financial risk management by offering investors, portfolio managers, and regulatory bodies in emerging markets a robust tool for volatility forecasting that maintains consistent accuracy across different market regimes, from stable periods to high-volatility crises such as the COVID-19 market disruption. The study's methodological innovations, including parallel processing architecture, attention mechanisms, and regime-adaptive evaluation frameworks, advance the theoretical understanding of hybrid financial modeling while establishing a practical implementation framework that can enhance investment decision-making, portfolio optimization, and early warning systems for market turbulence. These findings not only contribute to the growing body of literature on hybrid econometric-machine learning approaches but also provide a foundation for future research exploring more sophisticated volatility prediction models and their applications in emerging market contexts, ultimately supporting more informed financial decision-making in increasingly complex global markets.

CRediT Authorship Contribution Statement

Rangga Kurnia Putra Wiratama: Conceptualization, Software, Formal analysis, Investigation, Resources, Data Curation, Writing – Original Draft, Writing – Review & Editing, Supervision. **Ahmad Saikhu**: Conceptualization, Methodology, Validation, Formal analysis, Resources, Writing – Review & Editing, Supervision, Project Administration, Funding Acquisition. **Nanik Suciati**: Conceptualization, Methodology, Validation, Formal analysis, Resources, Writing – Review & Editing, Supervision, Project Administration, Funding Acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

The dataset was openly provided [https://finance.yahoo.com].

Declaration of Generative AI and AI-assisted Technologies in The Writing Process

The authors used generative AI to improve the writing clarity of this paper. They reviewed and edited the AI-assisted content and take full responsibility for the final publication.

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