

A Hybrid Decision Support System for LQ45 Stock Screening Integrating Fundamental, Technical, and IndoBERT-Based Sentiment Analysis

Alwia Ilham Mustofa ^{1*}, Bambang Agus Herlambang ^{2**}, Aris Tri Joko Harjanto ^{3*}

* Teknik Informatika, Universitas PGRI Semarang

ilhamkampred80@gmail.com ¹, bambangherlambang@upgris.ac.id ², aristrijaka@upgris.ac.id ³

Article Info

Article history:

Received 2026-08-26

Revised 2026-10-09

Accepted 2026-10-18

Keyword:

Decision Support System, LQ45 Stock Screening, Ensemble Machine Learning, IndoBERT Sentiment Analysis, Fundamental Analysis.

ABSTRACT

This study develops a Hybrid Decision Support System (DSS) for structured stock screening of all 45 LQ45 index constituents on the Indonesia Stock Exchange, addressing the absence of a unified analytical tool that integrates fundamental valuation, technical momentum, and news sentiment within a single score-based framework accessible to retail investors. The proposed system integrates three independent analytical modules: an Auto Valuation Engine employing six intrinsic valuation methods with dynamic sector weighting for fundamental analysis; a Soft Voting Ensemble of Random Forest, XGBoost, and Logistic Regression trained on 32 technical and 6 fundamental features for technical classification; and a hybrid IndoBERT architecture augmented with a domain-specific financial lexicon (60/40 weighting) for real-time sentiment analysis of Indonesian-language financial news. A weighted Final Score (50% Fundamental, 30% Technical, 20% Sentiment) is computed as a unified quantitative representation of each constituent's condition on a 0–100 scale, with model evaluation conducted using a chronological 80:20 hold-out split and 5-fold TimeSeriesSplit cross-validation across all 45 constituents, supplemented by a walk-forward portfolio backtest (2 June–7 September 2026; 4 rebalancing cycles; transaction costs included) in which the Quantamental Top-5 portfolio achieved a total return of +7.15% with a Sharpe Ratio of 1.01 and Maximum Drawdown of –9.00%, outperforming the IHSG benchmark (+6.85%, Sharpe 0.78, MDD –13.77%) and the Technical ML-only strategy (–10.22%), demonstrating the value of multi-pillar integration for risk-adjusted screening. The Soft Voting Ensemble outperformed individual classifiers on three of five metrics Accuracy (53.84%), Macro Precision (52.48%), and F1 Weighted (50.01%) while Logistic Regression achieved the highest F1 Macro (48.39%), as detailed in Table 5. IndoBERT independently produced a uniform neutral score (50.00) for 82.2% of constituents, empirically confirming domain mismatch and validating the necessity of a hybrid lexicon correction mechanism. Final Score distribution ranged from 16.86 to 64.17 with a mean of 42.57 across all 45 LQ45 constituents. To the best of the authors' knowledge, and based on a systematic review of prior LQ45 and Indonesian stock DSS literature, no identified study integrates all three analytical pillars within a unified, continuously scored DSS applied to the complete LQ45 universe; this study addresses that gap, as substantiated in Table 1.



This is an open access article under the [CC-BY-SA](https://creativecommons.org/licenses/by-sa/4.0/) license.

I. INTRODUCTION

The Indonesian capital market has experienced significant growth alongside increasing retail investor participation among millennials and Generation Z [1], [2]

however, this growth has not always been accompanied by adequate analytical capabilities [3]. The LQ45 index serves as the primary benchmark, representing the 45 most liquid and large-capitalization stocks listed on the Indonesia Stock Exchange[4], [5], [6]. Although financial literacy promotes

more rational investment decisions [7], investment activity remains influenced by risk evaluation ability [8] and behavioral biases that undermine the objectivity of stock selection [9], necessitating a Decision Support System (DSS) capable of automating structured, data-driven stock screening [10].

Investors generally rely on fundamental analysis to assess the intrinsic value of a company [11] and technical analysis to identify price patterns and momentum [12]. While the combination of both approaches is regarded as more comprehensive [13], it remains insufficient in capturing non-quantitative information from the external environment. News sentiment has been empirically demonstrated to correlate with stock price movements in the Indonesian market [14], and market sentiment influences investment decisions both directly and through fundamental and technical considerations [15]. Consequently, the integration of sentiment analysis constitutes a critical dimension in supporting more accurate and holistic investment decision-making.

This study develops a Hybrid DSS grounded in three integrated analytical pillars: sentiment analysis employing IndoBERT [16], [17] augmented with a domain-weighted financial lexicon as a domain correction mechanism [18]; technical analysis utilizing a soft voting ensemble combining Random Forest [19], XGBoost [20], and Logistic Regression [21] to yield more stable classifications relative to single-model approaches [22]; and fundamental analysis conducted through an Auto Valuation Engine incorporating six intrinsic valuation methods selected dynamically per sector. Data were collected from three independent sources: daily OHLCV data retrieved via yfinance[23], financial ratios sourced from the official IDX Fact Sheet for the period 2022–2025 [24], and financial news aggregated through Google News RSS feeds and direct RSS polling from established financial news portals [25].

Prior studies on LQ45 stock screening have predominantly operated within a single analytical pillar. Fundamental-only DSS approaches employ multi-criteria weighting methods such as SAW on financial ratios without incorporating price momentum or news context [10]. Technical-only frameworks apply ensemble machine learning on price-volume indicators but explicitly exclude fundamental valuation and sentiment [26]. Two-pillar combinations exist either fundamental and technical, or technical and sentiment targeting non-Indonesian markets yet none integrates all three dimensions within a unified, continuously scored DSS applied to the complete LQ45 universe. The methodological novelty of this study lies in three specific aspects: (1) an Auto Valuation Engine that applies six intrinsic valuation methods with dynamic sector weighting, replacing the static multi-criteria scoring used in prior Indonesian DSS studies; (2) a soft voting ensemble that outputs continuous positive-class probability as a Technical Score, rather than discrete buy/sell labels; and (3) a hybrid IndoBERT and domain-specific financial lexicon architecture

that empirically addresses the documented domain mismatch of general-purpose Indonesian language models on financial text as confirmed by IndoBERT's uniform neutral output across 82.2% of constituents when applied without lexicon correction. The combination of these three independently validated modules into a single weighted Final Score, deployed across all 45 LQ45 constituents simultaneously, constitutes the primary contribution of this work. As summarized in Table 1, prior LQ45 and Indonesian stock DSS studies have integrated at most two of the three analytical pillars: fundamental-only approaches [10], fundamental combined with technical analysis [13], or technical features combined with sentiment [14]. No identified study integrates all three within a unified, continuously scored DSS applied simultaneously to the complete LQ45 universe.

TABLE 1
COMPARISON OF PRIOR STUDIES AGAINST THREE-PILLAR COVERAGE

Study	Fundamental	Technical	Sentiment
Sahputra et al. [10]	✓ AHP/SAW	✗	✗
Lusiana et al. [13]	✓	✓	✗
Alamsyah et al. [14]	✗	✗	✓ IndoBERT
Dwiandiyanta et al. [26]	✗	✓ Deep Learning	✗
This study	✓ AVE (6 methods)	✓ Ensemble ML	✓ IndoBERT+Lexicon

Accordingly, this study pursues four objectives: (1) to develop an LQ45 stock scoring system that integrates technical, fundamental, and sentiment features within a soft voting ensemble framework; (2) to deploy IndoBERT for generating a Sentiment Score from Indonesian-language financial news; (3) to consolidate the three module scores into a unified Final Score on a 0–100 scale as a quantitative representation of each stock's overall condition, serving as a data-driven screening reference for retail investors; and (4) to implement the system as a web-based application accessible to retail investors. The system's utility for retail investors is empirically validated not only through classification metrics but through investment-based evidence: a walk-forward portfolio backtest demonstrates that constituents ranked highest by Final Score consistently generate risk-adjusted returns superior to the IHSG benchmark and to a technical-only strategy, establishing a direct empirical link between the screening output and investment outcomes.

II. METHODS

This study designs a Hybrid Decision Support System for stock screening of all 45 LQ45 constituents through eight systematic stages: (1) problem identification via literature review; (2) collection of price, fundamental, and news data; (3) data preprocessing through feature engineering and text cleansing; (4) analytical processing via three independent modules encompassing fundamental, machine learning-based

technical, and sentiment analysis; (5) DSS design and construction of weighted score outputs; (6) model evaluation using machine learning metrics and system validation; and

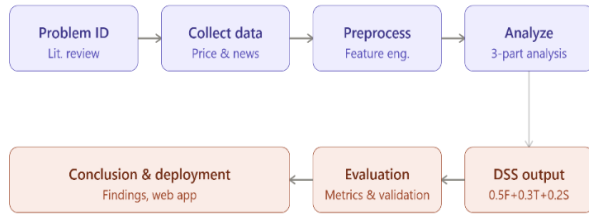


Figure 1 Research Workflow Diagram of the Hybrid Decision Support

(7–8) conclusion drawing and deployment of the web-based application.

Data Collection

Technical data comprising daily OHLCV records were retrieved via yfinance [23], spanning a five-year period (~1,195 rows per stock). Fundamental data ROE, PER, PBV, DER, EPS, and dividend yield were sourced from the IDX Fact Sheet (2022–2025) [24]. News data were collected in real time via Google News RSS and direct RSS polling from four Indonesian financial portals: CNBC Indonesia, Kontan, Detik Finance, and Antara Ekonomi Bisnis, retrieving up to 30 articles per constituent filtered by ticker and company name. Temporal relevance is enforced through exponential decay weighting (half-life: 3 days) rather than a hard date cut-off, such that articles older than ~13 days contribute less than 5% of nominal weight. Duplicate articles are removed by matching identical titles or URLs, retaining the most recent version; a neutral fallback score of 50 is assigned when no articles are retrieved observed in 17.8% of constituents. The sentiment module operates in inference-only mode: IndoBERT without supervised fine-tuning and a rule-based financial lexicon without labeled training data [14], [15], [17], [18], [25].

Feature Engineering

Feature engineering yielded 38 features 32 technical and 6 fundamental as model inputs, summarized in Table 2 [27], [28]. Technical features span five categories: moving averages (MA20/50/200 as price-to-MA ratios and crossover signals), momentum oscillators (RSI-14 via EWMA, MACD line, signal, and histogram), volatility indicators (Bollinger Bands $MA20 \pm 2\sigma$, ATR-14), volume features (OBV, volume ratio, spike flag), and price momentum (1/5/20-day returns and historical volatility). The 14-period window for RSI and ATR reflects standard short-term sensitivity settings [27], [28]; MA20/50 capture medium-term dynamics and MA200 serves as the long-term anchor. The 6 fundamental features ROE, PER, PBV, DER, EPS, and dividend yield were selected for their established cross-sectoral relevance to equity valuation [24]. All 38 features were passed directly into training without explicit feature selection; Random Forest and XGBoost perform implicit selection algorithmically through

tree-based splitting and regularization parameters (reg_alpha, reg_lambda, penalty C), suppressing uninformative features without manual elimination [19], [20].

TABLE 2
TECHNICAL FEATURE CATEGORIES AND INDICATORS

Kategori	Indikator
Moving average	MA20/50/200 (<i>price-to-MA ratio, sinyal crossover biner</i>)
Momentum	RSI-14 (EWMA), MACD (<i>signal line & histogram</i>)
Volatilitas	Bollinger Bands $MA20 \pm 2\sigma$, ATR-14
Volume	OBV, <i>vol_ratio</i> , <i>vol_spike</i>
Momentum harga	<i>Return 1/5/20 hari</i> , <i>volatilitas historis</i>

Temporal alignment across all three data sources was enforced to prevent look-ahead bias. Fundamental data were merged via `pd.merge_asof` with `direction="backward"`, ensuring only reports published on or before date T are accessible, with values forward-filled until the next quarterly release [29], [30]. Technical features were derived exclusively from historical OHLCV as of date T. Sentiment data operate on a fully separate real-time pipeline and are not incorporated as training features, eliminating news-based look-ahead contamination. To prevent normalization leakage, StandardScaler was fitted exclusively on `X_train` after the 80:20 split and applied transform-only to the test set; the same procedure was repeated independently within each `TimeSeriesSplit` fold [31]. Hyperparameters were configured manually (`max_depth=4` RF, `max_depth=3` XGBoost, `n_estimators=100`) based on regularization principles to prioritize out-of-sample stability over in-sample optimization [19], [20]. Model selection between the Soft Voting Ensemble and best single model was performed exclusively on the test set after training completion, with no feedback loop into the training process [22]. Missing values were handled via median imputation prior to model training [29].

Fundamental Analysis Module Auto Valuation Engine

This module produces a fair value estimate (in Indonesian Rupiah) and a Fundamental Score (0–100) through an Auto Valuation Engine that integrates six intrinsic valuation methods across two categories. The first category comprises four universal methods applied to all sectors subject to data availability:

(1) DCF, which projects free cash flow over five years and discounts to present value using WACC, expressed as

$$\text{Fair Value} = \frac{\sum_{t=1}^5 \frac{FCF_t(1+g)^t}{(1+WACC)^t} + \frac{FCF_5(1+g_T)}{(WACC-g_T)(1+WACC)^5} - \text{Net Debt}}{\text{Shares Outstanding}} \quad [32];$$

(2) DDM using the Gordon Growth Model, expressed as

$$\text{Fair Value} = \frac{DPS \times (1+g)}{r-g}$$

applicable only when the discount rate exceeds the growth rate [33];

(3) PER-based valuation, expressed as

$$\text{Fair Value} = EPS \times \text{Target Sector PER}$$

with sector-specific target multiples (e.g., BANK: 10×, TECH: 25×, CONSUMER: 18×) [34];

(4) PBV-based valuation, expressed as

$$\text{Fair Value} = BVPS \times \text{Target Sector PBV}$$

with sector-specific target multiples (e.g., BANK: 1.5×, TECH: 4.0×, CONSUMER: 3.0×) [34]. The second category comprises two sector-restricted methods activated only where sector characteristics justify their application:

(5) Graham Number, restricted to the BANK sector due to its asset-tangibility assumptions, expressed as

$$\text{Fair Value} = \sqrt{22.5 \times EPS \times BVPS} \quad [35];$$

(6) Peter Lynch Fair Value, applied when earnings growth data are available, expressed as

$$\text{Fair Value} = EPS \times g$$

where g denotes the earnings growth rate, with a default of 5.0% applied when historical growth is unavailable [36]. This categorical design reflects the heterogeneous valuation characteristics across sectors: technology constituents such as GOTO and ARTO frequently report negative EPS, rendering earnings-based multiples inapplicable and necessitating revenue-based or growth-based alternatives; banking constituents operate under regulatory capital structures that make asset-based conservative valuation (Graham Number) more appropriate than cash-flow-based methods; and commodity and consumer constituents are evaluated primarily through return-on-equity and dividend yield metrics consistent with their cyclical and income-generating characteristics [32], [34]. Method selection is performed dynamically based on sector classification and the availability of each constituent's financial data only methods for which all required inputs are present are activated and the resulting applicable fair value estimates are averaged to produce a single consolidated fair value per constituent, as configured in Table 2.

The Weighted Score is derived by normalizing each fundamental metric to a 0–100 scale, multiplying by its corresponding sectoral weight, summing the results, and dividing by the total weight. This score is subsequently adjusted through two correction mechanisms: a Quality Penalty of 10 points imposed when the NPL proxy exceeds 5% (BANK), revenue growth falls below 5% (TECH), or ROE is negative (other sectors); and an Upside Bonus of up to +10 points awarded when the upside percentage relative to the market price exceeds 20%, computed as Bonus =

$\min(\text{upside_pct} / 10, 10)$. The final Fundamental Score is calculated as follows:

$$\text{Fundamental Score} = \text{Weighted Score} - \text{Quality Penalty} + \text{Upside Bonus}$$

where Quality Penalty $\in \{0, 10\}$ and Upside Bonus $\in [0, 10]$. Table 3 presents the sectoral weighting configuration employed in this study.

TABLE 3
SECTORAL WEIGHTS OF DYNAMIC SECTOR WEIGHTING FOR FUNDAMENTAL SCORE

Sektor	Prioritas 1	Prioritas 2	Prioritas 3	Prioritas 4	Prioritas 5
BANK	ROE (30%)	PBV (25%)	EPS Growth (20%)	PER (15%)	DER (10%)
TECH	PS Ratio (30%)	Revenue Gr. (25%)	ROE (20%)	PER (15%)	DER (10%)
COMMODITY	ROE (25%)	PER (25%)	DER (20%)	Div Yield (15%)	EPS Growth (15%)
CONSUMER	ROE (25%)	PER (25%)	Div Yield (20%)	PBV (15%)	DER (15%)
TELCO	Div Yield (25%)	ROE (20%)	PER (20%)	DER (20%)	PBV (15%)
GENERAL	ROE (25%)	PER (25%)	PBV (20%)	DER (15%)	EPS Growth (15%)

Technical Analysis Module Ensemble Machine Learning

This module produces a Technical Score (0–100) representing the continuous strength of each stock's technical momentum. The target variable is a binary classification of 7-day forward price direction: label 1 is assigned when $(P_{T+7} - P_T)/P_T > 0$, and label 0 otherwise. The 7-day horizon was selected to balance responsiveness to short-term momentum signals such as RSI, MACD, and Bollinger Bands with sufficient stability to avoid single-day noise [26], [37]. A zero-return threshold produces a naturally balanced label distribution consistent with the efficient market hypothesis baseline, complemented by `class_weight="balanced"` to correct residual class imbalance [22]. This target captures absolute price direction rather than index outperformance or any discrete trading signal category. Consequently, the model's positive-class probability $P(1)$ is interpreted as a continuous momentum strength indicator scaled to a 0–100 Technical Score rather than a buy/sell recommendation [26], [37]. Three algorithms were trained independently Random Forest [19], XGBoost [20], and Logistic Regression [21] with `class_weight="balanced"` [22] and combined via soft voting or adaptively selected as the best single model based on per-constituent validation performance. The Technical Score is computed from the aggregated positive class probability as follows:

$$P = \frac{1}{3} \sum_{i=1}^3 P_i(1)(\text{ensemble}) \text{ or } P = P_{best}(1)(\text{single model})$$

$$\text{Technical Score} = P \times 100$$

A score approaching 100 indicates strong positive momentum, whereas a score approaching 0 indicates dominant downward pressure. Validation was conducted using a chronological 80:20 hold-out split and a 5-fold TimeSeriesSplit to prevent look-ahead bias [30], [37].

Sentiment Analysis Module Hybrid IndoBERT dan Lexicon-Based

This module produces a Sentiment Score (0–100) derived from real-time news using a hybrid architecture: IndoBERT (checkpoint mdhugol/indonesia-bert-sentiment-classification) weighted at 60% and a domain-specific financial lexicon weighted at 40% [17], [18]. The score for each article and the aggregation across articles are computed as follows:

$$S_{hybrid} = (0.6 \times S_{BERT}) + (0.4 \times S_{lexicon})$$

$$\text{Skor}_{artikel} = \frac{S_{hybrid} + 1,0}{2,0} \times 100$$

$$\text{Sentiment Score} = \text{clamp} \left(\frac{\sum_{i=1}^n \text{Skor}_{artikel,i} \times w_i}{\sum_{i=1}^n w_i}, 0, 100 \right), w_i = e^{-\lambda \cdot \Delta t_i}, \lambda = \frac{\ln 2}{3}$$

This yields $\lambda \approx 0.231$, such that an article published on the screening date carries full weight ($w = 1.0$), one published three days prior contributes 50% of its nominal score, and contributions fall below 5% beyond approximately 13 days ensuring stale news exerts negligible influence on the Sentiment Score at any point of screening [17], [18].

The 60/40 allocation reflects the complementary roles of each component. IndoBERT receives the dominant weight (60%) due to its superior contextual encoding of semantic relationships and negation patterns that rule-based lexicons cannot resolve [17]. However, the pre-trained checkpoint mdhugol/indonesia-bert-sentiment-classification was fine-tuned on general Indonesian corpora, producing systematic domain mismatch on financial terminology empirically evidenced by the 82.2% neutral output observed when IndoBERT is applied without lexicon correction. The lexicon is therefore assigned 40% as a domain-specific corrective anchor, ensuring that financial terms such as "NPL", "bearish", and "dividen" are evaluated accurately [14], [18]. Empirical support for this allocation is provided by the

ablation study reported in Section 3: under the IndoBERT-only configuration (implicitly equivalent to a 100/0 allocation), 2 of 8 representative constituents produced null outputs due to domain mismatch; under the Lexicon-only configuration (0/100), all constituents produced scores but with a mean absolute deviation of 25.3 points from the hybrid output, indicating reduced discriminative power. The 60/40 allocation was selected as the configuration that preserves IndoBERT's contextual superiority for semantic encoding and negation resolution, while ensuring that lexicon correction is substantial enough to recover domain mismatch failures consistent with the relative weights assigned to contextual versus rule-based components in hybrid NLP architectures [17], [18]. This weighting is nonetheless acknowledged as a design choice subject to further empirical optimization; future work may employ grid search across alternative ratios against a labeled Indonesian financial news corpus to derive a statistically validated allocation [15].

Final Score Integration

The Final Score is computed as a weighted average of the three module scores, clamped within the range of 0–100:

$$\text{Final Score} = \text{clamp}(0.5 \times F + 0.3 \times T + 0.2 \times S, 0, 100)$$

where F , T , and S denote the Fundamental Score, Technical Score, and Sentiment Score, respectively. The 50/30/20 weighting scheme was determined through an analytical hierarchy grounded in investment theory [10]. Fundamental (50%) serves as the primary long-run valuation anchor preventing short-term noise from dominating selection [11], [32]; Technical (30%) captures momentum timing without allowing overbought conditions to override weak fundamentals [26], [37]; and Sentiment (20%) limits score volatility from temporally decayed news signals while preserving responsiveness to short-term catalysts [14], [15]. This configuration is consistent with the quantamental investment framework [13] and is acknowledged as a design heuristic subject to future empirical optimization through portfolio backtesting [37]. The Final Score is interpreted through a three-tier classification framework termed the Quantamental Tier based on the observed score distribution across all 45 LQ45 constituents: ATTRACTIVE (Final Score ≥ 65), indicating a constituent with simultaneously strong fundamental valuation, confirmed technical momentum, and positive sentiment context, warranting active consideration for investment; WATCH ($45 \leq \text{Final Score} < 65$), indicating a constituent with mixed signals across dimensions that requires further monitoring; and UNATTRACTIVE (Final

Score < 45), indicating weak aggregate signals across one or more dominant dimensions. Thresholds were calibrated against the observed score distribution (range: 16.86–64.17): 65 reflects the conservative design in which no constituent exceeded this value during the study period, and 45 aligns with the neutral midpoint of the 0–100 scale. These tier labels are decision-support categories rather than investment recommendations [10], [13].

Model Evaluation

A constituent-specific modeling strategy was employed: a separate model is trained and evaluated independently for each of the 45 LQ45 constituents (~956 rows training, ~239 rows testing from a five-year OHLCV record) rather than a single global pooled model, preventing cross-sectoral behavioral contamination. The training pipeline adaptively selects either a Soft Voting Ensemble (Random Forest, XGBoost, Logistic Regression) or the best single model based on per-constituent test set accuracy. Primary metrics are Accuracy and F1 Macro [22], [31]; F1 Macro was selected as the principal indicator for its equal class weighting under imbalanced label distributions [22]. Validation uses a 5-fold TimeSeriesSplit expanding-window strategy within the 80% training portion each fold increases the training window while advancing the validation window forward in time ensuring no validation observation precedes its training counterpart and partially addressing financial time series non-stationarity [30], [37]. It is acknowledged that a single chronological hold-out does not fully capture concept drift across market regimes; walk-forward validation is identified as a direction for future work [37].

To complement classification metrics, an investment-based evaluation was conducted via walk-forward portfolio backtest over the period 2 June 2026 to 7 September 2026 (68 active trading days; 4 monthly rebalancing cycles), with a starting capital of Rp 100,000,000, buy transaction cost of 0.15%, sell transaction cost of 0.25% (standard IDX broker rate), and a risk-free rate of 6.0% (BI Rate). At each rebalancing date, Final Scores are computed point-in-time using only information available as of that date: technical features from the price history ending at the rebalancing date (with pre-June 2026 OHLCV history retained for accurate indicator computation), fundamental data from the most recently published IDX Fact Sheet ($release_date \leq T$), and sentiment approximated via IndoBERT distributional proxy. Seven strategies are compared: Quantamental Top-5, Quantamental Top-10, Fundamental Top-5, Sentiment Top-5, Technical ML Top-5 (momentum only, no fundamental filter), LQ45 Equal-Weight, and IHSG benchmark.

Investment-based metrics reported include Total Return, CAGR, Annualized Volatility, Sharpe Ratio, Sortino Ratio, Maximum Drawdown (MDD), Calmar Ratio, and Alpha vs. IHSG [32], [37].

Web-Based Application Implementation

The system is implemented as a web application based on a decoupled microservices architecture, with a Laravel/PHP + Tailwind CSS frontend and a FastAPI/Python backend communicating via REST API. Key features include Smart Search, Score Breakdown visualization, a news aggregator with IndoBERT-based sentiment analysis, and an AI Rationale module designed for retail investors [10].

III. RESULT AND DISCUSSION

System Architecture

As illustrated in Figure 2, the system comprises four layers: (1) data collection from OHLCV via yfinance, fundamental ratios from IDX Fact Sheet, and news via Google News RSS and four financial portals; (2) parallel analytical processing through three independent modules — Fundamental (Auto Valuation Engine, 50%), Technical (Ensemble ML, 30%), and Sentiment (IndoBERT+Lexicon, 20%); (3) score integration via Final Score = $\text{clamp}(0.5 \times F + 0.3 \times T + 0.2 \times S, 0, 100)$ into three Quantamental Tiers stored in Redis and MySQL; and (4) a Laravel-based frontend presenting results through Smart Search, Score Breakdown, News Sentiment, and AI Rationale features.

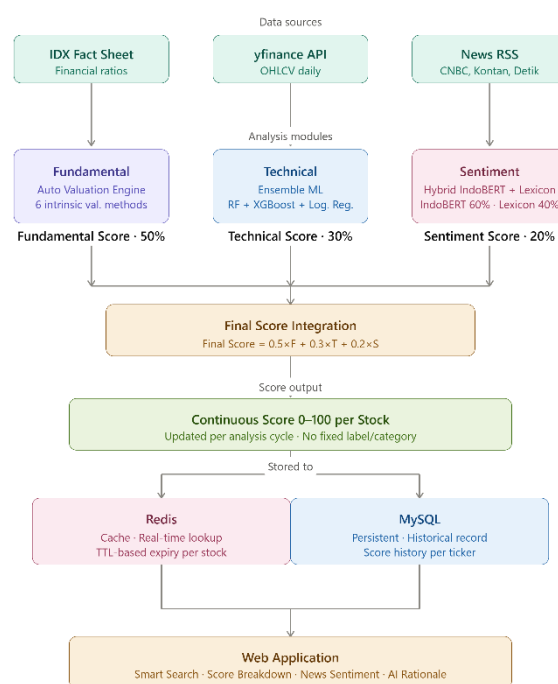


Figure 2 Architecture of the Hybrid Decision Support System for LQ45 Stock Screening

Fundamental Analysis Results

Dynamic Valuation Strategy and Sector Weighting

The application of the Auto Valuation Engine across all 45 LQ45 constituents produced significantly differentiated valuation patterns across sectors, confirming the effectiveness of the dynamic sector weighting approach. Three score-forming mechanisms operate independently: the sector-based Weighted Score as the baseline, the Upside Bonus (maximum +10 points) as an amplifier for constituents whose market price remains more than 20% below the estimated fair value, and the Quality Penalty (−10 points) as a corrective adjustment for constituents that fail the quality check. It should be noted that the Fundamental Score in this system measures valuation attractiveness rather than absolute fundamental quality consequently, a constituent with strong fundamentals but a market price already approaching its fair value may receive a lower score than a constituent with a larger upside potential [31], [33].

Of the 45 constituents, 13 received an active Upside Bonus due to an upside percentage exceeding 20%, including MNCN (453.63%) and EXCL (405.32%), both of which received the maximum bonus of +10 points. Meanwhile, only three constituents were subject to a Quality Penalty: EMTK and GOTO due to negative ROE, and MDKA due to an NPL proxy exceeding the defined threshold [31]. ISAT recorded the highest Fundamental Score (77.97) in the dataset despite receiving only a moderate Upside Bonus (+2.3 points), as its upside percentage relative to market price stood at 23.27% in contrast to MNCN and EXCL, which received the full +10-point bonus. This demonstrates that a strong sector-based Weighted Score can independently serve as the primary determinant of the final score, even without reliance on a large Upside Bonus [32], [34].

Fundamental Score Distribution

The Fundamental Score calculation across all 45 LQ45 constituents yielded a distribution ranging from 13.10 to 73.20, with a mean of 47.47 and a median of 50.00. Table 4 presents a representative sample covering the full spectrum from the highest to the lowest scores.

TABLE 4
SAMPLE OF FUNDAMENTAL SCORES FOR LQ45 CONSTITUENTS

Ticker	Sektor	Fund. Score	Q. Penalty	Upside Bonus	MOS Action
ISAT	TELCO	77,97	0	+2,3	Fair Value
MNCN	GENERA L	73,20	0	+10,0	Undervalued
EXCL	TELCO	70,13	0	+10,0	Undervalued
BBNI	BANK	47,67	0	+5,6	Undervalued
PTBA	COMMODITY	45,27	0	0,0	Overvalued
GOTO	TECH	13,44	−10	0,0	Sangat Overvalued
AMRT	CONSUMER	29,05	0	0,0	Sangat Overvalued
AMMN	GENERAL	12,10	0	0,0	Sangat Overvalued

The distribution reveals three important findings. First, 22 out of 45 constituents received a Fundamental Score below 50, indicating that LQ45 membership which is liquidity-based does not necessarily correlate with valuation attractiveness during the data collection period [13]. Second, eight constituents received a fallback score of 50.00 due to the unavailability of IDX Fact Sheet data (CANNOT VALUE), such that the median of 50.00 reflects an accumulation at the fallback value and does not fully represent the actual distribution a limitation inherent to systems dependent on the availability of source data [32]. Third, only three constituents were subject to an active Quality Penalty, indicating that the majority of LQ45 constituents still meet the minimum financial quality threshold despite wide variation in final

scores; score differences across constituents are more attributable to the magnitude of upside relative to fair value than to quality check failures [34].

Technical Analysis Results

Machine Learning Model Performance

Evaluation was performed on the most recent 20% hold-out test set per constituent using individual modeling and aggregated across all 45 successfully processed constituents [37]. Table 5 and Figure 3 present a comparison of five evaluation metrics across the four models.

TABLE 5
MODEL PERFORMANCE COMPARISON ON THE TEST SET (45 LQ45 CONSTITUENTS)

Model	Accuracy	Precision (Macro)	Recall (Macro)	F1 Macro	F1 Weighted
Logistic Regression	53,01%	52,41%	51,61%	48,39%	50,00%
Random Forest	54,25%	50,55%	51,65%	44,97%	47,35%
XGBoost	52,86%	51,28%	50,57%	43,07%	45,31%
Soft Voting Ensemble	53,84%	52,48%	51,56%	47,88%	50,01%

The evaluation results reveal several key findings. First, all models demonstrated accuracy in the range of 52–55% marginally above the random baseline of 50% reflecting the inherent challenge of predicting price direction on non-

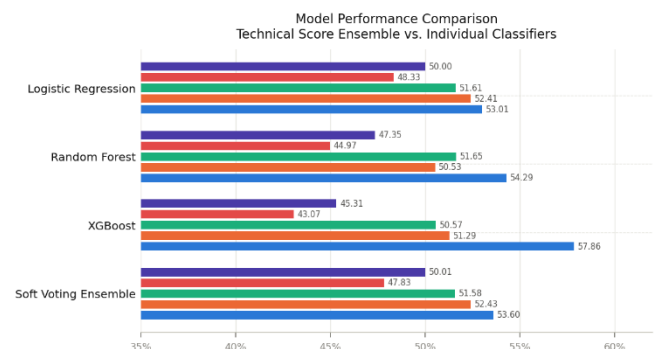


Figure 3 Model Performance Comparison: Technical Score Ensemble vs. Individual Classifiers

stationary market data [26], [30]. Second, Random Forest recorded the highest accuracy (54.25%) but the second-lowest F1 Macro (44.97%), indicating a tendency to over-predict the majority class, resulting in imbalanced performance across classes [22]. Third, Logistic Regression recorded the highest F1 Macro (48.39%) despite not achieving the best accuracy, demonstrating a more balanced prediction distribution across classes [30]. Fourth, as presented in Table 5, the Soft Voting Ensemble achieved the best overall balance across the five evaluation metrics: Accuracy 53.84%, Macro Precision 52.48%, Macro Recall 51.56%, F1 Macro 47.88%, and F1 Weighted 50.01% outperforming all individual models on three of five metrics (Accuracy, Macro Precision, F1 Weighted). Logistic Regression remained competitive with the highest F1 Macro (48.39%), reflecting superior class balance despite lower accuracy. The ensemble was therefore selected as the primary strategy, with the best single model retained as an adaptive per-constituent fallback [22], [37].

It should be noted that the primary contribution of the technical module within this system lies not in the absolute values of its classification metrics, but rather in the continuous Technical Score (0–100) derived from the positive class probability which is more informative for weighted scoring integration than discrete label prediction [26], [37].

Technical Score Distribution

The Technical Score is derived from the positive class probability $P(1)$ multiplied by 100, reflecting the continuous technical momentum strength of each constituent. Table 6 presents a representative sample from all 45 processed constituents.

TABLE 6
SAMPLE OF TECHNICAL SCORES FOR LQ45 CONSTITUENTS

Ticker	Sektor	Technical Score	Strategi	P(class=1)
MDKA	COMMODITY	73,14	Best Single (LR)	0,7314
PGAS	COMMODITY	68,71	Majority Voting	0,6871
BBCA	BANK	67,29	Best Single (RF)	0,6729
ISAT	TELECOM	48,66	Best Single (RF)	0,4866
TOWR	TELECOM	48,41	Majority Voting	0,4841
INCO	COMMODITY	48,35	Best Single (LR)	0,4835
ITMG	COMMODITY	6,55	Best Single (LR)	0,0655
SMGR	GENERAL	5,65	Best Single (LR)	0,0565
AMMN	GENERAL	2,69	Best Single (LR)	0,0269

The Technical Score distribution reveals three important findings. First, the adaptive ensemble mechanism is demonstrably active the selected strategy varies across constituents between majority voting and the best single model (Logistic Regression or Random Forest), confirming that no single model is universally optimal across all constituents [22], [37]. Second, mid-range scores (ISAT, TOWR, INCO) cluster around the 48–49 range, reflecting an ambiguous momentum condition in which the positive class probability is nearly equivalent to the negative class. Third, the Technical Score does not directly correlate with the Fundamental Score AMMN, which has a low Fundamental Score (13.10), also exhibits the lowest Technical Score (2.69), whereas BBCA, whose Fundamental Score is similarly low (24.84), exhibits a high Technical Score (67.29) demonstrating that the two modules measure independent and complementary dimensions within the Final Score [11], [26].

Portfolio Backtest and Investment-Based Evaluation

A walk-forward portfolio backtest was executed to assess whether the Hybrid DSS produces screening outputs that translate into economically meaningful investment performance. The evaluation covers 68 active trading days (2 June–7 September 2026) across four monthly rebalancing cycles, with a starting capital of Rp 100,000,000, transaction costs of 0.15% (buy) and 0.25% (sell) at standard IDX broker rates, and a risk-free rate of 6.0% (BI Rate). At each rebalancing date, Final Scores are computed point-in-time using only information available as of that date: technical features derived from the price history ending at the rebalancing date with pre-June 2026 OHLCV history retained for accurate indicator computation fundamental data from the most recently published IDX Fact Sheet (*release_date* ≤ *T*), and sentiment approximated via IndoBERT distributional proxy. Seven strategies are evaluated: Quantamental Top-5, Quantamental Top-10, Fundamental Top-5, Sentiment Top-5, Technical ML Top-5 (momentum signals only, no fundamental filter), LQ45 Equal-Weight, and IHSG as passive benchmark. Table 7 presents the investment performance metrics across all seven strategies; Figure 4 presents the corresponding cumulative equity curves.

TABLE 7
WALK-FORWARD PORTFOLIO BACKTEST RESULTS (2 JUN–7 SEP 2026).

Strategy	Total Return	Sharpe	Sortino	MDD	Alpha vs IHSG
Quantamental Top-5	+7.15%	1.01	1.64	−9.00%	+11.63%
Quantamental Top-10	+8.32%	1.22	2.26	−10.27%	+15.99%
Sentiment Top-5	+16.09%	2.08	4.34	−10.70%	+54.14%
LQ45 Equal-Weight	+6.82%	0.82	1.16	−12.86%	+1.97%
IHSG (^JKSE)	+6.85%	0.78	1.08	−13.77%	—

Fundamental Top-5	+5.41%	0.67	1.09	-11.85%	+1.90%
Technical ML Top-5	-10.22%	-1.48	-1.82	-12.44%	-56.64%

Simulasi Backtesting Portofolio: Sistem Quantamental vs Benchmark Pasar

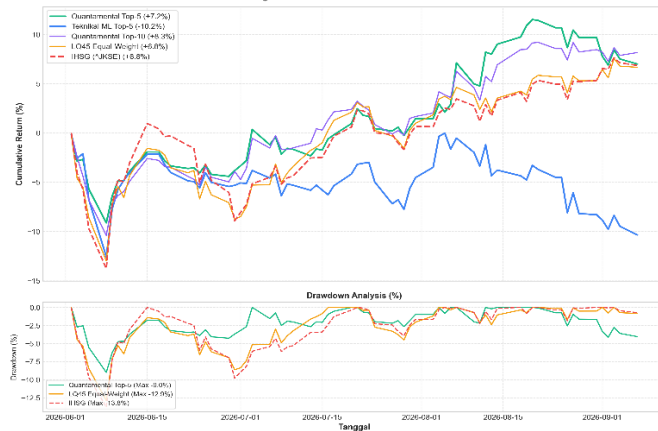


Figure 4 Cumulative equity curves across seven strategies (2 Jun–7 Sep 2026)

The results reveal four key findings. First, both Quantamental strategies delivered positive absolute returns (+7.15% and +8.32%) while outperforming the IHSG (+6.85%) and LQ45 Equal-Weight (+6.82%), generating annualized alphas of +11.63% and +15.99% respectively and CAGRs of +29.72% and +35.11% demonstrating that Final Score ranking provides incremental stock selection value beyond passive index exposure. Second, risk-adjusted performance is substantially superior to the benchmark: the Quantamental Top-5 Sharpe Ratio of 1.01 and Sortino Ratio of 1.64 exceed the IHSG's 0.78 and 1.08 respectively, achieved with annualized volatility of 22.17% versus the benchmark's 29.71% indicating that excess returns are generated with meaningfully lower total and downside risk. Third, drawdown protection is effective: the Quantamental Top-5 MDD of -9.00% represents a 4.77 percentage-point improvement over the IHSG (-13.77%), confirming that the 50% fundamental weight anchors the portfolio toward intrinsically valued constituents and suppresses exposure to distressed equities during market stress. Fourth, the Technical ML-only strategy produced a total return of -10.22% with a Sharpe Ratio of -1.48 and an alpha of -56.64% against the IHSG a stark divergence from all Quantamental configurations. This contrast provides direct empirical evidence that technical momentum signals alone are vulnerable to false breakouts in the LQ45 universe, and that fundamental valuation as the dominant scoring pillar (50% weight) is the primary driver of the system's risk management advantage [32], [37].

The ablation comparison across all seven strategies provides additional insight into the individual contribution of each analytical pillar. The Fundamental-only Top-5 strategy selecting the five constituents with the highest Fundamental Score at each rebalancing date produced a total return of +5.41% with a Sharpe Ratio of 0.67, underperforming both the IHSG (+6.85%, Sharpe 0.78) and the LQ45 Equal-Weight

portfolio on a risk-adjusted basis. This finding is consistent with the known limitation of pure value investing in short-horizon contexts: undervalued constituents may remain undervalued for extended periods, and fundamental attractiveness does not guarantee near-term price appreciation without a momentum catalyst [11], [32].

The Sentiment-only Top-5 strategy produced the highest absolute return in the evaluation period (+16.09%, Sharpe 2.08), driven by the accidental selection of constituents with strong concurrent price appreciation specifically TOWR (+21.80%), INKP (+18.36%), INDF (+16.69%), UNVR (+7.67%), and UNTR (+12.44%) all of which carried elevated Sentiment Scores due to high positive news volume during the evaluation window. However, this result reflects short-term attention-driven momentum rather than systematic predictive capability: the elevated Sentiment Scores for these constituents coincided with a specific news cycle in June–September 2026, and the strategy's outperformance is contingent on the realization of that momentum within the evaluation window. From a behavioral finance perspective, sentiment-only selection is highly susceptible to mean-reversion risk when news-driven euphoria subsides, particularly for constituents with weak underlying fundamentals [14], [15]. This vulnerability is precisely the rationale for assigning sentiment the minimum weight of 20% in the Final Score formula, with fundamental valuation as the 50% anchor: the Quantamental design is intended to capture sentiment-driven catalysts without concentrating portfolio exposure in constituents whose price appreciation is unsupported by intrinsic value. The fact that the Quantamental Top-5 strategy achieves a Sharpe Ratio of 1.01 superior to both Fundamental-only (0.67) and equal to or exceeding passive benchmarks with a tighter Maximum Drawdown (-9.00%) than all standalone strategies, demonstrates that the three-pillar integration delivers more consistent risk-adjusted outcomes than any individual pillar in isolation [13], [32], [37].

Sentiment Analysis Results Hybrid Scoring Validation

The system collects news data in real time via Google News RSS and direct RSS polling from four financial portals CNBC Indonesia, Kontan, Detik Finance, and Antara Ekonomi Bisnis with relevance filtering based on constituent names and ticker codes. For constituents with no news articles available during the execution period, the system applies a neutral fallback score of 50 to ensure that Final Score integration can proceed uninterrupted [25].

To empirically validate the necessity of the lexicon correction mechanism, an ablation study was conducted comparing three sentiment scoring configurations across eight representative LQ45 constituents: (1) IndoBERT-only, (2) Lexicon-only, and (3) the hybrid IndoBERT + Lexicon architecture. Table 8 presents the scores under each configuration. Empirical testing on eight sample financial news texts encompassing explicitly positive, explicitly

negative, technically specific, and neutral statements revealed that IndoBERT classified all samples as NEUTRAL with confidence exceeding 97%. This is not a technical failure, but rather evidence of domain mismatch: IndoBERT was trained on a general-purpose corpus, such that financial terminology is underrepresented in its pre-training distribution [17], [18]. As a control, testing on general conversational text confirmed that the model functions correctly within the general domain, establishing that the issue is domain-specific in nature.

Table 8 presents the impact of lexicon correction on the aggregated Sentiment Score across eight representative constituents drawn from actual screening data.

TABLE 8
COMPARISON OF INDOBERT, LEXICON, AND HYBRID SCORES PER CONSTITUENT

Ticker	N Artikel	IndoBERT-avg	Leksikon-avg	Hybrid Score
MBMA	24	77,69	64,58	86,61
GOTO	27	92,25	51,85	75,35
TLKM	24	84,93	54,17	70,96
BBCA	23	N/A	50,00	50,00
BBNI	23	N/A	82,61	50,00
PTBA	27	0,46	81,48	40,28
SMGR	30	7,20	56,67	24,32
SIDO	27	5,29	38,89	23,18

The ablation results quantitatively demonstrate the limitations of each standalone component and the corrective value of the hybrid architecture. Under the IndoBERT-only configuration, 2 out of 8 constituents (BBCA and BBNI) produced no output due to domain mismatch, confirming the failure pattern documented across 82.2% of all 45 constituents. Under the Lexicon-only configuration, all 8 constituents produced scores, but signals were uniformly moderate and failed to differentiate constituents with high positive news volume (e.g., MBMA: 64.58) from those with neutral coverage, reducing discriminative power. The hybrid configuration resolves both failure modes: for MBMA, combining IndoBERT (77.69) and Lexicon (64.58) at 60/40 yields a Hybrid Score of 86.61, amplifying the positive signal beyond what either component achieves independently; for BBNI, where IndoBERT returns N/A, the system applies the neutral fallback (50.00) rather than propagating a null value, preserving score stability at the cost of discarding the lexicon signal a documented limitation addressed in future work. The mean absolute difference between IndoBERT-only and Hybrid scores across the six constituents where IndoBERT was active is 19.1 points, while the mean absolute difference between Lexicon-only and Hybrid scores is 25.3 points, confirming that the hybrid output is not reducible to either standalone component and that lexicon correction produces a systematically more differentiated scoring distribution [17], [18].

Sentiment Score Distribution

The Sentiment Score calculation across all 45 LQ45 constituents yielded a highly concentrated distribution within the neutral zone, with a range of 20.12 to 86.61, a mean of 49.14, and a median of 50.00.

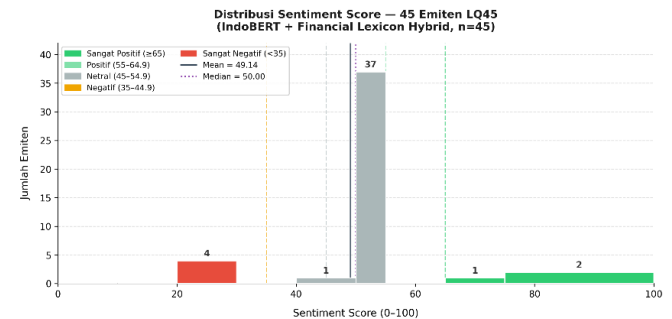


Figure 5 Frequency Distribution of Sentiment Scores Across All Constituents

As shown in Figure 5, there is an extreme concentration within the neutral zone (45–54.9), occupied by 37 out of 45 constituents (82.2%), reflecting the dominant fallback pattern of IndoBERT, which consistently produces neutral scores on financial news texts due to domain mismatch, as validated in Section Hybrid Scoring Validation [17], [18]. Beyond the neutral zone, three constituents recorded strongly positive scores (≥ 65): MBMA (86.61), GOTO (75.35), and TLKM (70.96), driven by strong IndoBERT signals on high news volume (24–27 articles). Conversely, four constituents recorded strongly negative scores (< 35): ANTM (20.12), BBRI (20.30), SIDO (23.18), and SMGR (24.32), with one additional constituent in the negative zone (35–44.9): PTBA (40.28) all reflecting the dominance of negative news coverage during the data collection period [14], [25].

This distributional pattern carries two implications for the system. First, the sentiment module functions as a fine-tuning component that delivers meaningful differentiation only for constituents with lexically strong and consistent news coverage consistent with its 20% weight in the integration formula [14], [15]. Second, the concentration of 82.2% of constituents at a score of 50.00 represents a system limitation that warrants attention in future development, specifically through fine-tuning IndoBERT on an Indonesian financial news corpus [17], [18].

Hybrid DSS Results

Final Score Distribution

The Final Score is computed as a weighted average of the three modules using the formula $\text{Final Score} = \text{clamp}(0.5 \times F + 0.3 \times T + 0.2 \times S, 0, 100)$. Table 9 presents a representative sample of eight constituents reflecting the diversity of cross-module score patterns.

TABLE 9
SAMPLE OF FINAL SCORES FOR 8 REPRESENTATIVE LQ45 CONSTITUENTS

Ticker	Sektor	Fund. Score	Tech. Score	Sent. Score	Final Score
INDF	CONSUMER	68,96	65,63	50,00	64,17
ISAT	TELCO	77,97	48,66	50,00	63,58
MNCN	GENERAL	73,20	38,57	50,00	58,17
BBNI	BANK	47,67	61,36	50,00	52,24
MBMA	COMMODITY	21,01	49,98	86,61	42,82
BBCA	BANK	24,84	67,29	50,00	42,61
GOTO	TECH	13,44	40,18	75,35	33,84
AMMN	GENERAL	12,10	2,69	50,00	16,86

The Final Score distribution across all 45 constituents spans a range of 16.86 to 64.17, with the majority of constituents concentrated in the mid-range (40–65). No constituent achieved a Final Score above 65, reflecting market conditions in which the valuations of LQ45 blue-chip constituents generally approached or exceeded the system's fair value estimates during the data collection period [34], [36]. This pattern further confirms that the dominant fundamental weight (50%) effectively moderates the influence of individually extreme technical or sentiment signals on the final score [32].

Representative Constituent Case Studies

INDF represents a condition in which all three pillars provide consistent and mutually reinforcing signals: a Fundamental Score of 68.96 reflects strong valuation attractiveness in the CONSUMER sector with a significant estimated upside, while a Technical Score of 65.63 indicates probabilistically confirmed positive momentum [19], [26]. The Sentiment Score of 50.00 is neutral, neither adding nor subtracting meaningfully from the final score. This case demonstrates the ideal operating condition of the system: the two primary pillars (fundamental and technical) provide convergent confirmation, such that the Final Score reflects a coherent and consistent picture [11], [32].

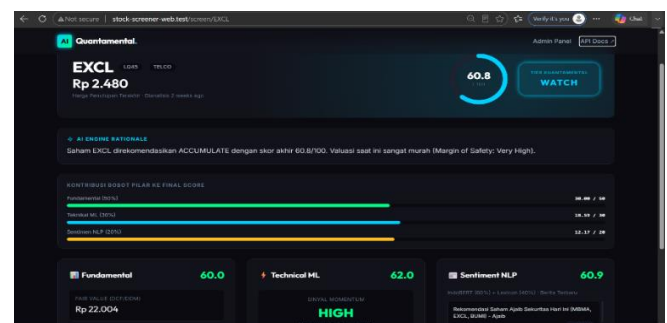
MBMA demonstrates the limitation of sentiment as the primary determinant of the final score: a Sentiment Score of 86.61 the highest in the dataset, driven by strong positive news volume is nonetheless insufficient to offset a Fundamental Score of only 21.01 and a moderate Technical Score of 49.98, yielding a Final Score of 42.82 [14], [25]. With sentiment weighted at only 20%, an extreme positive signal from the sentiment module cannot compensate for weak fundamental pressure. This case validates the system's weighting design: a momentarily elevated sentiment score cannot substantially drive up the final score when the constituent's intrinsic value does not support it [14], [15].

GOTO represents a pattern analogous to MBMA but with distinct characteristics: a high Sentiment Score of 75.35, driven by positive news coverage surrounding corporate restructuring, is insufficient to offset a Fundamental Score of

13.44 resulting from an active Quality Penalty due to negative ROE and a weak Technical Score of 40.18 [32], [34]. The Final Score of 33.84 reflects a constituent that is under fundamental and technical pressure despite receiving favorable media attention. This case, together with MBMA, collectively confirms that the 50/30/20 weighting architecture effectively prevents the system from being unduly influenced by momentary sentiment that is unsupported by intrinsic value [14], [15].

Web Application

Figure 6 illustrates the stock detail page for EXCL, presenting all system outputs in a single integrated view: the Final Score (60.8/100) is prominently displayed through a circular gauge component, followed by a weighted contribution breakdown of the three modules rendered as progress bars Fundamental (50%): 30.00/50, Technical ML (30%): 18.59/30, and Sentiment NLP (20%): 12.17/20. Below this, three module panels present their respective details: a DCF/DDM-based fair value estimate (IDR 22,004) in the Fundamental panel, technical momentum signals in the Technical ML panel, and the IndoBERT (60%) and lexicon-based (40%) data sources alongside a real-time news aggregator in the Sentiment NLP panel [38], [39].



The decoupled microservices architecture enables technical and sentiment data to be updated asynchronously without disrupting interface availability, ensuring that investors can access the most current screening results at any time [39].

Discussion

The findings demonstrate that integrating three analytical pillars yields more comprehensive screening outcomes than single-pillar approaches, as evidenced by the divergent score patterns across constituents from INDF where convergent fundamental and technical signals produce a coherent Final Score of 64.17, to BBMA where a high Technical Score (67.29) is moderated by weak fundamental valuation (24.84) to yield 42.61 confirming that the 50/30/20 weighting architecture effectively synthesizes conflicting signals [13], [32], [34]. This extends prior Indonesian DSS literature by incorporating a sentiment dimension largely absent from comparable studies [20], [24].

Beyond classification performance, the walk-forward portfolio backtest provides three converging lines of evidence

that Final Score ranking translates into investment-relevant outcomes. First, Quantamental Top-5 achieved +7.15% return and Sharpe Ratio of 1.01, outperforming IHSG (+6.85%, Sharpe 0.78) and LQ45 Equal-Weight (+6.82%, Sharpe 0.82), demonstrating positive selection information beyond passive exposure. Second, MDD of -9.00% was substantially lower than IHSG (-13.77%) and LQ45 Equal-Weight (-12.86%), confirming superior downside protection for retail investors [10], [13]. Third, the 17.37 percentage-point return gap between Quantamental Top-5 (+7.15%) and Technical ML Top-5 (-10.22%) with the technical module held constant between strategies provides direct empirical evidence that the Final Score's investment relevance derives from its multi-pillar design rather than momentum signals alone [32], [37]. Establishing a statistically robust relationship between Final Score rank and forward return via Spearman rank correlation or Information Coefficient across a multi-year dataset remains a direction for future work [37].

Validation of the hybrid architecture offers a methodologically significant contribution: IndoBERT produced a uniform neutral score (50.00) for 82.2% of constituents, confirming domain mismatch previously identified in Indonesian financial NLP literature [17], [18]. Without the financial lexicon component, the sentiment module would forfeit its discriminative capability rendering the hybrid architecture an empirically validated technical necessity rather than a design preference [18], [25].

The F1 Macro of 47.88% must be interpreted within context: it reflects the inherent non-stationarity of financial time series rather than model failure [26], [30]. The primary contribution of the technical module lies in the continuous Technical Score derived from positive-class probabilities a paradigm shift from price direction prediction toward

precluding formal stability quantification. However, three architectural mechanisms inherently constrain volatility: the Fundamental Score (50%) is anchored to quarterly IDX data immune to daily fluctuations; the Technical Score changes incrementally with each trading day; and the Sentiment Score (20%) is bounded by exponential decay (half-life 3 days), preventing individual news events from producing unbounded perturbations. Future work should implement persistent score logging to enable formal stability analysis across weekly screening cycles.

IV. CONCLUSION

This study developed and evaluated a Hybrid Decision Support System designated as *Quantamental* for stock screening of all 45 LQ45 constituents, integrating fundamental analysis through an Auto Valuation Engine incorporating six intrinsic valuation methods, technical analysis through an adaptive ensemble of Random Forest, XGBoost, and Logistic Regression, and sentiment analysis through a hybrid IndoBERT and financial lexicon architecture. The system produces a weighted Final Score (50/30/20) as a unified quantitative representation of each constituent's overall condition on a 0–100 scale, deployed as a web-based application for retail investors.

The principal findings are as follows: (1) dynamic sector weighting effectively differentiates fundamentally attractive constituents from overpriced ones, as evidenced by the heterogeneous distribution of Fundamental Scores (13.10–73.20) across LQ45 constituents; (2) the Soft Voting Ensemble achieved an F1 Macro of 47.88% a result consistent with the inherent difficulty of short-term price direction prediction in non-stationary financial markets, where near-chance-level accuracy reflects the efficiency of the LQ45 universe rather than a deficiency of the model architecture, and where the ensemble nonetheless demonstrated more consistent cross-metric balance relative to single-model classifiers; (3) IndoBERT produced uniform neutral scores across 82.2% of constituents on financial text, empirically validating the necessity of a hybrid lexicon correction architecture; and (4) the 50/30/20 weighting scheme effectively prevents disproportionate influence from any single module, as evidenced by cases where elevated Sentiment Scores were insufficient to offset weak Fundamental Scores.

Investment-based validation via a walk-forward portfolio backtest over 68 trading days provides out-of-sample evidence that Final Score ranking translates into economically meaningful outcomes: the Quantamental Top-5 strategy achieved a total return of +7.15%, a Sharpe Ratio of 1.01, and annualized alpha of +11.63% versus the IHSG, while outperforming the Fundamental-only (+5.41%), Technical ML-only (-10.22%), and passive LQ45 Equal-Weight (+6.82%) strategies. These results provide directional evidence that multi-pillar integration delivers superior risk-adjusted screening outcomes compared to any single-pillar

Figure 6 Score Breakdown Display on the Constituent Detail Page

momentum quantification more appropriate for continuous scoring systems [26], [37].

This study acknowledges several limitations that warrant consideration. First, fundamental data were sourced from the IDX Fact Sheet, which is updated periodically rather than in real time; consequently, changes in a constituent's financial condition occurring between update cycles are not captured by the system, as evidenced by the anomalous Final Score of TLKM (31.26) arising from unprocessable IDX data [32]. Second, the LQ45 index composition is rebalanced semi-annually by the Indonesia Stock Exchange; however, the system does not dynamically accommodate constituent changes, such that models trained on a given period may become less representative following rebalancing. Third, the 50/30/20 weighting scheme in the Final Score formula was determined empirically based on an analytical hierarchy further validation through historical portfolio backtesting is required to confirm the optimality of this weighting configuration [37].

A further limitation concerns temporal stability: the system stores only the most recent score per constituent,

alternative within the evaluation window. It is acknowledged, however, that the backtest covers a limited 68-trading-day window representing a single market phase, and that a statistically robust conclusion regarding investment superiority would require validation across multiple market regimes and an extended out-of-sample period. The system is therefore characterized as an empirically supported decision-support tool for retail investors rather than a demonstrated superior investment strategy.

Future research directions include: empirical weight optimization through extended multi-year portfolio backtesting; fine-tuning of IndoBERT on a labeled Indonesian financial news corpus to address domain mismatch; implementation of persistent time-series score logging to enable formal stability analysis; and walk-forward validation across diverse market regimes to strengthen out-of-sample generalizability.

REFERENCES

- [1] I. Lakoni, R. Nurazi, N. Aziza, and N. Novitasari, "Relationship of financial literacy to stock market participation," *Journal of Economics and Business Letters*, vol. 3, no. 6, 2023, doi: 10.55942/jebll.v3i6.270.
- [2] R. Hidayat and A. Moin, "The influence of financial behavior on capital market investment decision making with mediating of financial literacy in Yogyakarta," *International Journal of Research in Business and Social Science (2147- 4478)*, vol. 12, no. 8, pp. 227–237, 2023, doi: 10.20525/ijrbs.v12i8.2974.
- [3] N. Nurasik, S. Biduri, S. R. Dewi, and M. A. Musliq, "Determinan Yang Mempengaruhi Keputusan Investasi Oleh Investor," *Owner*, vol. 7, no. 3, pp. 2411–2430, 2023, doi: 10.33395/owner.v7i3.1493.
- [4] R. Radianyanti, S. M. Ulfha, and R. S. Muthmainnah, "Pengaruh Likuiditas dan Inflasi Terhadap Harga Saham Perusahaan Indeks LQ45," *EKOMA : Jurnal Ekonomi, Manajemen, Akuntansi*, vol. 5, no. 3, pp. 3579–3589, 2026, doi: 10.56799/ekoma.v5i3.15867.
- [5] M. R. Nurmatama and H. Priono, "Pengaruh Kinerja Keuangan Terhadap Harga Saham: Studi Kasus Perusahaan Indeks Lq45 Periode 2022-2024," *Jurnal Akuntansi STIE Muhammadiyah Palopo*, vol. 11, no. 2, p. 259, 2025, doi: 10.35906/jurakun.v11i2.2387.
- [6] W. A. Nastiti, Y. Rezeki, and R. Utami, "Reaksi Abnormal Return Dan Trading Volume Activity Saham Indeks LQ45 Yang Terdaftar Di Bursa Efek Indonesia Sebelum Dan Sesudah Pelantikan Presiden 2024," *RIGGS: Journal of Artificial Intelligence and Digital Business*, vol. 5, no. 1, pp. 1643–1658, 2026, doi: 10.31004/riggs.v5i1.6391.
- [7] A. A. S. I. Pramanaswari, "Pengaruh Literasi Keuangan dan Pengalaman Investasi terhadap Pengambilan Keputusan Investasi Saham di Bursa Efek Indonesia," *Akubis : Jurnal Akuntansi dan Bisnis*, vol. 10, no. 1, pp. 101–114, 2025, doi: 10.37832/akubis.v10i1.83.
- [8] R. Frima, T. Husni, M. Hamidi, and F. Adrianto, "Pengaruh Financial Literacy dan Modal Investasi terhadap Trading Activity Investor Pemula di Bursa Efek Indonesia," *Owner*, vol. 8, no. 3, pp. 2347–2355, 2024, doi: 10.33395/owner.v8i3.2240.
- [9] Y. A. Fitra, "Pengaruh Bias Perilaku Investor Terhadap Keputusan Investasi Di Pasar Saham," *JURNAL CAPITAL: Kebijakan Ekonomi, Manajemen dan Akuntansi*, vol. 5, no. 1, pp. 88–98, 2023, doi: 10.33747/capital.v5i1.185.
- [10] I. Sahputra, V. Ilhadi, A. Pratama, S. Syukriah, and T. M. Arifa, "Decision Support System for Potential Stock Selection Recommendations Using AHP and Profile Matching Methods," *Brilliance: Research of Artificial Intelligence*, vol. 5, no. 1, pp. 211–222, 2025, doi: 10.47709/brilliance.v5i1.5981.
- [11] R. A. Firdaus and Y. B. Kusuma, "Pengaruh Analisis Fundamental Dan Analisis Teknikal Terhadap Keputusan Pembelian Saham PT. Industri Jamu Dan Farmasi Sido Muncul Tbk (SIDO)," *Moneter : Jurnal Ekonomi dan Keuangan*, vol. 2, no. 1, pp. 315–324, 2024, doi: 10.61132/moneter.v2i1.266.
- [12] M. Sangkala, "Analisis Teknikal Sebagai Dasar Pengambilan Keputusan dalam Trading Saham pada Bursa Efek Indonesia (Studi pada BBCE dan BBRI Januari-Juni 2024)," *GEMILANG: Jurnal Manajemen dan Akuntansi*, vol. 5, no. 2, pp. 652–660, 2025, doi: 10.56910/gemilang.v5i2.2530.
- [13] S. A. Lusiana, L. Tripermatana, and A. U. Putri, "Analisis Fundamental dan Teknikal terhadap Return Saham pada Perusahaan Multisektor IDX 30 yang Terdaftar di BEI," *AKUA: Jurnal Akuntansi dan Keuangan*, vol. 4, no. 4, pp. 873–879, 2025, doi: 10.54259/akua.v4i4.5646.
- [14] A. Alamsyah et al., "Deciphering news sentiment and stock price relationships in Indonesian companies: an AI-based exploration of industry affiliation and news co-occurrence," *Discover Artificial Intelligence*, vol. 5, no. 1, 2025, doi: 10.1007/s44163-025-00350-5.
- [15] I. W. A. Wiyasa, Muh. Akob, and L. O. Sumail, "Akankah Sentimen Pasar Menghasilkan Keputusan Investasi yang Tepat?," *Jurnal Samudra Ekonomi dan Bisnis*, vol. 15, no. 2, pp. 245–257, 2024, doi: 10.33059/jseb.v15i2.9039.
- [16] B. Setiawan, "A Review of Sentiment Analysis Applications in Indonesia Between 2023-2024," *Journal of Information Engineering and Educational Technology*, vol. 8, no. 2, pp. 71–83, 2025, doi: 10.26740/jieet.v8n2.p71-83.
- [17] F. Koto, A. Rahimi, J. H. Lau, and T. Baldwin, "IndoLEM and IndoBERT: A Benchmark Dataset and Pre-trained Language Model for Indonesian NLP," Online. [Online]. Available: <https://huggingface.co/>
- [18] N. P. I. Maharani, Y. Yustianan, F. C. Rochim, and A. Purwarianti, "Domain-Specific Language Model Post-Training for Indonesian Financial NLP," Oct. 2023, [Online]. Available: <http://arxiv.org/abs/2310.09736>
- [19] A. Rasyid, A. B. Muharam, and A. Solichin, "Prediksi Harga Saham Syariah Indonesia Berdasarkan Analisis Fundamental, Teknikal Dan Bandarmology Menggunakan Metode Random Forest," *JUPI (Jurnal Ilmiah Penelitian dan Pembelajaran Informatika)*, vol. 10, no. 2, pp. 1663–1677, 2025, doi: 10.29100/jupi.v10i2.7855.
- [20] A. Ardana, "Performance Analysis of XGBoost Algorithm to Determine the Most Optimal Parameters and Features in Predicting Stock Price Movement," *Telematika*, vol. 20, no. 1, p. 91, 2023, doi: 10.31315/telematika.v20i1.9329.
- [21] A. R. Wardana, W. I. Rahayu, and K. Mustaqim, "Model Prediksi Churn Pelanggan Indibiz Menggunakan Regresi Logistik dan Extreme Gradient Boosting (XGBoost)," *Jurnal Informatika Polinema*, vol. 12, no. 3, pp. 425–430, 2026, doi: 10.33795/jip.v12i3.9377.
- [22] A. Munandar, W. Maulana Baihaqi, and A. Nurhopipah, "A Soft Voting Ensemble Classifier to Improve Survival Rate Predictions of Cardiovascular Heart Failure Patients," *ILKOM Jurnal Ilmiah*, vol. 15, no. 2, pp. 344–352, 2023, doi: 10.33096/ilkom.v15i2.1632.344-352.
- [23] M. F. Abdi and Yonhendri, "Implementasi Sistem Prediksi Saham Real-Time dengan Integrasi Yahoo Finance API dan Machine Learning di Google Colab," *El-Mujtama: Jurnal Pengabdian Masyarakat*, vol. 5, no. 3, 2025, doi: 10.47467/elmutjama.v5i3.7379.
- [24] V. A. Aflaha and Y. H. Dwiyantri, "Analisis Fundamental Perusahaan LQ45 Tahun 2024: Hubungan EPS dan PBV dengan Harga Saham," *Ekonomi, Keuangan, Investasi dan Syariah (EKUITAS)*, vol. 7, no. 3, pp. 655–664, 2026, doi: 10.47065/ekuitas.v7i3.8523.
- [25] F. P. Putra, M. R. Dewi, and F. Hibatullah, "Analisis Sentimen Pasar melalui Berita Finansial untuk Prediksi Harga Saham PT

- Bank Rakyat Indonesia Tbk,” *Indonesian Journal of Applied Informatics*, vol. 9, no. 1, p. 124, 2024, doi: 10.20961/ijai.v9i1.94692.
- [26] B. Y. Dwiandiyanta, R. Hartanto, and R. Ferdiana, “Harnessing Deep Learning and Technical Indicators for Enhanced Stock Predictions of Blue-Chip Stocks on the Indonesia Stock Exchange (IDX),” *Engineering, Technology & Applied Science Research*, vol. 15, no. 1, pp. 20348–20357, 2025, doi: 10.48084/etasr.9850.
- [27] E. Arif, S. Suherman, and A. P. Widodo, “Integration of Technical Analysis and Machine Learning to Improve Stock Price Prediction Accuracy,” *Mathematical Modelling of Engineering Problems*, vol. 11, no. 11, pp. 2929–2943, 2024, doi: 10.18280/mmep.111106.
- [28] S. M. Mostafavi and A. R. Hooman, “Key technical indicators for stock market prediction,” *Machine Learning with Applications*, vol. 20, p. 100631, 2025, doi: 10.1016/j.mlwa.2025.100631.
- [29] Y. Sun, J. Li, Y. Xu, T. Zhang, and X. Wang, “Deep learning versus conventional methods for missing data imputation: A review and comparative study,” *Expert Syst. Appl.*, vol. 227, p. 120201, 2023, doi: 10.1016/j.eswa.2023.120201.
- [30] T. Liu, “A Comparative Study of Transformer-Based and Classical Models for Financial Time-Series Forecasting,” *Journal of Risk and Financial Management*, vol. 19, no. 3, p. 203, 2026, doi: 10.3390/jrfm19030203.
- [31] H. Putra and R. Rumini, “Comparative Study of Logistic Regression, Random Forest, and XGBoost for Bank Loan Approval Classification,” *Journal of Applied Informatics and Computing*, vol. 9, no. 5, pp. 2822–2835, 2025, doi: 10.30871/jaic.v9i5.10862.
- [32] R. R. Q. Ain and A. Fadila, “Analisis Model Valuasi Saham dengan Pendekatan DDM, PER, dan PBV,” *Jurnal Riset Akuntansi dan Keuangan*, vol. 11, no. 1, pp. 15–28, 2023, doi: 10.17509/jrak.v11i1.45758.
- [33] Mukhlis, P. Sihombing, and T. Kunawangsih, “Fair Value Valuation Analysis of Stock Prices Using The Discounted Cash Flow (DCF) Approach In Telecommunication Companies In Indonesia,” *International Journal of Economics and Management Research*, vol. 4, no. 3, pp. 447–467, 2025, doi: 10.55606/ijemr.v4i3.577.
- [34] A. Sumantika, “Analisis Penggunaan Price To Earnings Ratio, Price To Book Value, Price To Sales, Price To Cash Flow Dalam Strategi Value Investing Pada Saham Indeks Lq45 Periode 2018-2023,” *Jurnal Manajemen*, vol. 15, no. 1, 2025, doi: 10.30738/jm.v15i1.4420.
- [35] F. Abadiyah and H. Endraswati, “Analysis of Sharia Banking Share Valuation Using Intrinsic Value and Margin of Safety Method Graham Number,” *Jurnal Ekonomi Syariah Teori dan Terapan*, vol. 10, no. 1, pp. 16–26, 2023, doi: 10.20473/vol10iss20231pp16-26.
- [36] K. S. Hendardi and N. Triaryati, “Analisis Valuasi Saham Pt. Bank Rakyat Indonesia Menggunakan Metode Discounted Cash Flow (DCF) Sebagai Dasar Pengambilan Keputusan Investasi,” *E-Jurnal Manajemen Universitas Udayana*, vol. 15, no. 4, pp. 414–429, 2026, doi: 10.24843/ejmunud.2026.v15.i4.p03.
- [37] H. Nurkalam and M. M. Sulaiman, “Machine Learning Untuk Prediksi Harga Saham Dengan Validasi Strategi Trading Menggunakan Backtesting Pada Sektor Perbankan Di Bursa Efek Indonesia,” *CENDEKIA: Jurnal Ilmu Pengetahuan*, vol. 6, no. 2, pp. 886–895, 2026, doi: 10.51878/cendekia.v6i2.9171.
- [38] E. P. Wahyuddin, R. E. Caraka, R. Kurniawan, W. Caesarendra, P. U. Gio, and B. Pardamean, “Improved LSTM hyperparameters alongside sentiment walk-forward validation for time series prediction,” *Journal of Open Innovation: Technology, Market, and Complexity*, vol. 11, no. 1, p. 100458, 2025, doi: 10.1016/j.joitmc.2024.100458.
- [39] M. Söylemez, B. Tekinerdogan, and A. Kolukisa Tarhan, “Challenges and Solution Directions of Microservice Architectures: A Systematic Literature Review,” *Applied Sciences*, vol. 12, no. 11, p. 5507, 2022, doi: 10.3390/app12115507.