International Journal of Computational and Experimental Science and ENgineering (IJCESEN)

Vol. 11-No.2 (2025) pp. 3127-3138
http://www.ijcesen.com

ISSN: 2149-9144

Research Article

Stress Testing Financial Systems– Simulating economic disruption using AI-driven risk models

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Article Info:

DOI: 10.22399/ijcesen.2132
Received : 21 January 2025
Accepted : 05 May 2025

Keywords :

Artificial Intelligence
Machine learning
Risks
Economic changes
Geopolitics
Predictive analysis

Abstract:

The increasing interconnectedness and complexity of global financial markets have increased the stakes for advanced risk assessment methods. Traditional financial stress testing based on static rule-based models, historic datasets, and past crisis data which is poorly suited to address the nonlinear relationships and rapidly evolving risk factors characteristic of modern economies. This paper explores the use of Artificial Intelligence (AI) in financial stress testing with machine learning (ML), deep reinforcement learning (DRL), and generative AI to simulate systemic economic shocks and predict financial instability better. It also considers social media activities, geopolitical situations, climate change, pandemics, global financial markets, emerging technologies. This study provides a mechanized AI-based implementation plan for financial stress testing, data engineering pipeline profiling, model selection methodologies (LSTMs, GANs, and XGBoost), and real-time risk monitoring approaches. Financial institution case studies such as the Federal Reserve, Bank of England, and hedge funds such as BlackRock show how AI enhances prediction accuracy, reduces risk assessment cycles, and provides real-time financial crisis management approaches. In addition, this paper also opens up the prospects of Quantum AI, DeFi risk modeling, and digital twins powered by AI to revolutionize systemic risk analysis and crisis forecasting in finance. Our findings show that AI-powered financial stress tests are capable of significantly enhancing risk resilience, early warning, and global financial stability. Studies on XAI methods, audit architectures under regulatory directives, and the combination of quantum computing with AI-powered financial modeling for enhancing financial sector risk assessment even further is a direction that should be explored in future research.

1. Introduction

Stress testing is a procedure of stimulating economic scenarios to evaluate financial performance. In simple terms, Stress testing is a risk management tool used to evaluate how financial institutions, stock market, banks, or specific assets might perform under extreme but plausible adverse conditions. The goal is to identify vulnerabilities and assess the resilience of financial systems or entities to withstand economic shocks.

1.1 Background

Stress testing focuses on Credit risk, Market Risk, Loans, and Liquid funds within any financial institute. Financial institutions started using stress testing in the early 1990s. However, the relevance of stress testing increased as a serious risk management tool after the Lehman Brother crisis in 2008. This was the first time global financial institutes and markets were majorly affected.
Stress testing emerged as a major risk management tool in the financial world, particularly after some

big financial crises revealed the fragility of financial systems. One can trace its development and application through some milestone events:
Early Beginnings: Banks and other financial institutions employed stress testing initially to assess the impact of stressful market conditions on their portfolios. It gained popularity in the 1990s when banks and regulators realized the need for more sophisticated risk management processes.

1997 Asian Financial Crisis: The crisis exposed weaknesses in financial systems and demonstrated the importance of analyzing how institutions could withstand extreme economic shocks.

2000 Dot-Com Bubble: The collapse of the technology stock bubble showed the risks of asset price volatility and the need for stress tests to measure market risks.

2007-2008 Global Financial Crisis (GFC): The GFC was a turning point for stress testing. The crisis blindsided many financial institutions, and its intensity led to huge failures and bailouts.
Regulators realized the significance of systemic stress testing in ensuring financial system stability.

Post-Crisis Regulatory Reforms: In the aftermath of the GFC, regulators across the world introduced enhanced stress testing requirements.
Such examples include the U.S. Dodd-Frank Act Stress Testing (DFAST) and Comprehensive Capital Analysis and Review (CCAR), and the European Banking Authority (EBA) stress tests.

1.2 Stress Testing Models and their evolution

Stress testing financial models has evolved significantly over time. New technologies, new financial schemes, global stock market connectivity, crypto currency, has added increased complexity in recent years with regards to financial markets and lessons learned from past crises. Below is the overview of previous testing models and how they evolved to what it is today. A/B testing can lead to improvements (Jain A. 2025)

1. Early Models (Pre-1990s)

- **Focus**: Simple sensitivity analysis, often on single risk factors like interest rates or exchange rates.
- **Limitations**: Static, lacked integration of risks, and ignored systemic effects.

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2. Post-1990s: Scenario Analysis

- **Trigger**: Crises like the 1997 Asian Financial Crisis and LTCM collapse.
- **Development**: Introduction of scenario-based testing, incorporating multiple risk factors.

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3. Post-2000: Integration of Risks

- **Trigger**: Dot-com bubble and early 2000s recession.
- **Development**: Models began combining market and credit risks, though liquidity and systemic risks were still underrepresented.

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4. Post-2008 Global Financial Crisis: Systemic Focus

- **Trigger**: The 2007-2008 crisis exposed systemic vulnerabilities.
- **Key Developments**:
  - **Macro Stress Testing**: Assessing macroeconomic shocks (e.g., GDP decline, unemployment).
  - **Reverse Stress Testing**: Identifying failure scenarios.
  - **Liquidity Risk**: Added to models.
  - **Dynamic Feedback**: Accounting for interactions between institutions and the economy.
- **Regulatory Push**: Mandates like Basel III and Dodd-Frank required regular stress testing for major institutions.

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5. Advanced Technologies

- **Technologies**: Use of machine learning and data mining.
- **Data Analysis**: Increasing use of data analysis tools like Power BI, Tableau, etc.
- **Granularity**: High-frequency, detailed data for more precise analysis.

2.Literature Review and Advancements

This research paper explores the transformative advancements in stress testing and expands its scope to more real-world recent problems that might affect financial institutions in the future. This paper focuses on areas like:

2.1 Below are the additional advancements

A. Technologies: Use of Artificial Intelligence, advanced Datasets, Machine Learning Models for better predictions.

Artificial Intelligence (AI) and Machine Learning (ML):

- AI and ML are revolutionizing stress testing through more accurate predictions, dynamic scenario generation, and real-time analysis.
- Both these technologies help uncover complex patterns and correlations that could evade traditional models, improving risk assessment and decision-making.

Advanced Datasets:

- Use of high-frequency, granular data sets allow for more precise and granular stress testing.
- Big data analytics allow institutions to incorporate a wider range of variables, from macroeconomic variables to micro-level transactional data.

B. **New Risks**: Incorporation of climate risk, cyber risk, and ESG (Environmental, Social, and Governance) factors.

Climate Risk:

- Stress tests also carry climate risks today, i.e., physical risks (e.g., natural disasters) and transition risks (e.g., regulation changes to shift to lower-carbon environment).
- Financial institutions employ tests to better anticipate climate change impacts on portfolios on an extended horizon of view.

Cyber Risk:

- As digitalization rises, cyber risk is also included in today's stress tests.
- Models simulate cyberattacks like data breach, ransomware, and downtime to establish financial and operational impacts.

ESG (Environmental, Social, and Governance) Considerations:

- ESG is also integrated increasingly into designs of stress tests to establish sustainability, social responsibility, and corporate governance risks.
- This is prompted by heightened investor inte rest in ESG factors and by regulators' mandates.

C. **Global Coordination:** Models now account for cross-border risks and spillovers.

Cross-Border Risks and Spillovers:

- Modern stress tests also consider global financial markets' integration, how shock can propagate from region to region.
- Of particular interest to multinational institutions and regulators that have to ensure global financial stability is

Regulatory Harmonization:

- Efforts are underway to synchronize stress test standards across jurisdictions, enabling greater co-ordination and management of risks on a global scale.

D. **Real-Time Testing**: Faster, more dynamic assessments.

Real-Time Stress Testing:

- Advance level computing power and near real-time dataset are making it easier to perform real-time stress testing.
- This allows markets and institutions to quickly access dip/growth.

Dynamic Scenarios:

- Stress testing rules have also become increasingly dynamic, taking into view newly emerging risks such as geopolitical tensions, wars, and pandemics.
- Such conditions provide better real-life insight into how financial systems can cope up with sharp intense shocks.

E. **Complex and Emerging Scenarios:** Including geopolitical risks, wars, pandemics, and emerging threats.

Geopolitical Risks and Wars:

- Stress testing also takes into consideration situations like geopolitical conflicts, trade wars, and sanctions, which can have significant impacts on global markets.

Pandemics and Health Crises:

- The COVID-19 pandemic gave the world an example and a need to incorporate health crises into stress testing frameworks.
- Models now evaluate the economic and financial impacts of pandemics, including disruptions to supply chains and labor markets.

F. **Social media**: Monitoring social media trading groups, trends, sentiments, and activities.

Monitoring Social Media:

- Social media platforms and trading groups are increasingly influencing market behavior. Ex. Case of Reddit group hyping GameStop.

- Stress testing models incorporate sentiment analysis and trend monitoring to assess how social media-driven trading activities can impact financial markets.
- This includes evaluating the risks of market manipulation, herd behavior, and misinformation.

G. **Cryptocurrency**: Monitoring cryptocurrency and how they affect financial institutes.

Cryptocurrency Risks:

- The rise of cryptocurrencies and digital assets has introduced new risks, such as volatility, regulatory uncertainty, and cybersecurity threats.
- Stress testing models are being adapted to assess how cryptocurrency market fluctuations can affect traditional financial institutions and systemic stability.
- This includes evaluating the impact of crypto market crashes, regulatory changes, and the integration of digital assets into mainstream finance.

2.2 Scope of the Paper

The paper is offering an overall discussion of emerging trends of stress tests and how they will have implications on markets, regulators, and financial institutions. The scope of this is enumerated below:

- An overview of technological trends of AI, big data, and ML on stress testing.
- An inquiry into how emerging risks of climate, cyber, and ESG are integrated into stress test framework.
- An inquiry into global cooperation measures along with cross-border management challenges of risks.
- An exploration of real-time tests, dynamic scenarios, along with social media and cryptocurrency impacts on financial risks

2.3 Contribution to the Paper

The aim of this research paper is to:

- Highlight the evolving role of technology and data in modern stress tests.
- Provide insight into how emerging risks are rewriting practice around stress tests.
- Sketch out what is on the horizon concerning the evolving face of stress tests, including challenges and pay-offs of global cooperation, real-time monitoring, and evolving market dynamics.

Through its discussion of these important issues, this paper contributes to financial stability debate, managing risk, and innovation regulation in an increasingly complex, integrated global context.

1. Framework for Modern Stress Testing

3.1 Core Components

A. **Data Collection and Integration:**
- Gather data from diverse sources like financial markets, macroeconomic indicators, social media, cryptocurrency markets, ESG metrics, and climate data.
- Use APIs, web scraping, and IoT sensors for real-time data ingestion.

B. **Risk Identification and Scenario Design:**
- Identify risks with market, credit, liquidity, climate, cyber, ESG, geopolitical, etc.
- Design scenarios like recession, pandemic, cyberattack, crypto crash using historical data, expert judgment, and predictive analytics.

C. **Modeling and Simulation:**
- Use AI/ML models for predictive analytics and dynamic scenario generation.
- Incorporate feedback loops to simulate interactions between financial institutions and the broader economy.

D. **Real-Time Monitoring and Analysis:**
- Continuously monitor market conditions, social media sentiment, and cryptocurrency trends.
- Use natural language processing (NLP) to analyze social media and news for early warning signals.

E. **Reporting and Decision Support:**
- Generate actionable items and stress test results for regulators, risk managers, and executives.
- Provide dashboards and visualizations for easy interpretation.

F. **Regulatory Compliance and Global Coordination:**
- Ensure compliance with regulatory frameworks (e.g., Basel III, Dodd-Frank).
- Share insights and coordinate with global regulators to address cross-border risks.

3.2 Working Model

Step 1: Data Collection

- Inputs:
  - Financial data (e.g., stock prices, interest rates, loan portfolios).
  - Macroeconomic data (e.g., GDP, unemployment, inflation).
  - Alternative data (e.g., social media sentiment, cryptocurrency prices, ESG scores).
  - Climate data (e.g., temperature, carbon emissions).
- Technologies:
  - APIs, web scraping, IoT sensors, and blockchain for data collection.

Step 2: Risk Identification and Scenario Design

- Process:
  - Use AI/ML to identify emerging risks and correlations.
  - Design scenarios (e.g., 20% market crash, 5% GDP contraction, ransomware attack).
- Technologies:
  - Machine learning algorithms for pattern recognition.
  - Monte Carlo simulations for scenario generation.

Step 3: Modeling and Simulation

- Process**:**
  - Apply AI/ML models to simulate the impact of scenarios on financial institutions.
  - Incorporate feedback loops to capture systemic interactions.
- Technologies**:**
  - Deep learning for predictive analytics.
  - Agent-based modeling for systemic risk assessment.

Step 4: Real-Time Monitoring

- Process**:**
  - Continuously monitor data streams for early warning signals.
  - Use NLP to analyze social media and news for sentiment and trends.
- Technologies**:**
  - Real-time data processing frameworks (e.g., Apache Kafka, Spark).
  - NLP tools (e.g., GPT, BERT) for sentiment analysis.

Step 5: Reporting and Decision Support

- Process**:**
  - Generate stress test results and risk assessments.
  - Provide dashboards and visualizations for stakeholders.
- Technologies**:**
  - Business intelligence tools (e.g., Tableau, Power BI).
  - Automated report generation using AI.

Step 6: Regulatory Compliance and Coordination

- Process**:**
  - Ensure compliance with regulatory requirements.
  - Share insights with global regulators to address cross-border risks.
- Technologies**:**
  - Blockchain for secure data sharing.
  - Cloud-based platforms for collaboration.

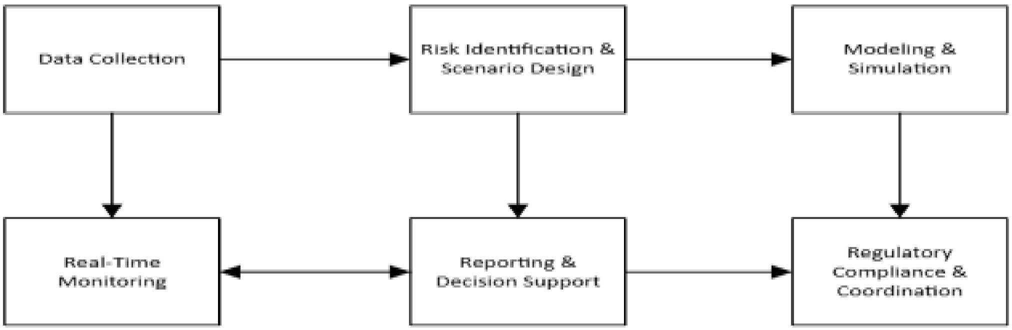

Figure 1. *Workflow diagram for stress testing model*

3.3 Functionality

1. **Data Integration:**
   - Collect and integrate data from multiple sources in real-time.
2. **Risk Assessment:**
   - Identify and prioritize risks using AI/ML algorithms.
3. **Scenario Simulation:**
   - Simulate the impact of adverse scenarios on financial institutions and markets.
4. **Real-Time Monitoring:**
   - Continuously monitor data streams for early warning signals.
5. **Reporting and Visualization:**
   - Generate actionable insights and visual reports for stakeholders.
6. **Regulatory Compliance:**
   - Ensure compliance with global regulatory standards and facilitate coordination.

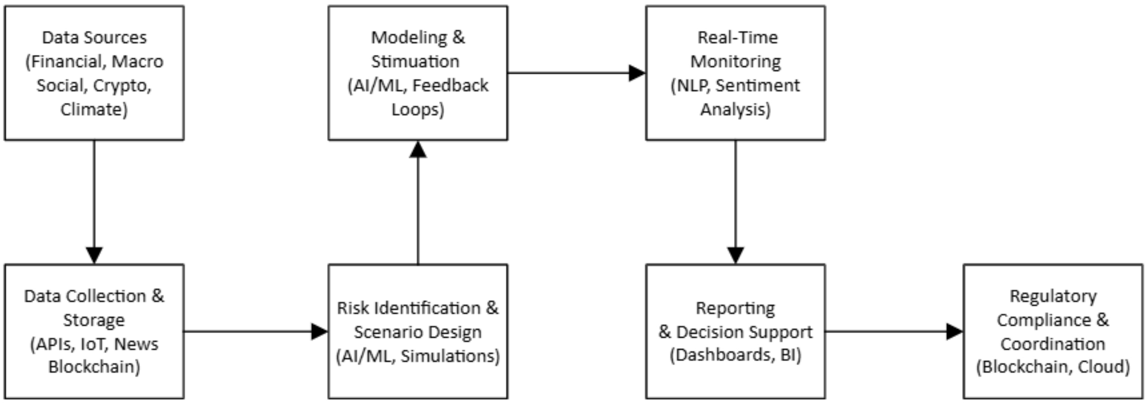

Figure 2. *Dataflow diagram for stress testing model*

3.4 Recommended Datasets

1. Financial and Macroeconomic Data

- **Yahoo Finance API**:
  - Provides historical and real-time stock prices, indices, and financial data.
  - Yahoo Finance
- **FRED (Federal Reserve Economic Data)**:
  - Offers macroeconomic data (e.g., GDP, unemployment, inflation).
  - FRED
- **World Bank Open Data**:
  - Global economic and financial indicators.
  - World Bank

2. Climate Risk Data

- **NASA's Global Climate Change Data**:
  - Historical and projected climate data.
  - NASA Climate Data
- **CDP (Carbon Disclosure Project)**:
  - ESG and climate-related data for companies and cities.
  - CDP

3. Social Media Sentiment Data

- **Twitter API**:
  - Access real-time tweets for sentiment analysis.
  - Twitter Developer
- **Reddit Datasets**:
  - Historical Reddit posts and comments for trend analysis.
  - Kaggle Reddit Datasets

4. Cryptocurrency Data

- **CoinGecko API**:
  - Real-time and historical cryptocurrency prices and market data.
  - CoinGecko
- **CryptoCompare**:
  - Comprehensive cryptocurrency data, including social sentiment.
  - CryptoCompare

5. Cybersecurity Data

- **CVE (Common Vulnerabilities and Exposures)**:
  - Database of cybersecurity vulnerabilities.
  - CVE
- **Kaggle Cybersecurity Datasets**:
  - Datasets on cyber threats, breaches, and attacks.
  - Kaggle Cybersecurity

3.5 Code Snippets

1. Data Collection

```
import yfinance as yf
import pandas as pd

# Fetch stock data from Yahoo Finance
stock_data = yf.download("AAPL", start="2020-01-01", end="2023-01-01")
print(stock_data.head())

# Fetch macroeconomic data from FRED
from fredapi import Fred
fred = Fred(api_key='your_api_key')
gdp_data = fred.get_series('GDP')
print(gdp_data.head())

```

2. Social Media Sentiment Analysis

```
from textblob import TextBlob
import tweepy

# Twitter API setup
consumer_key = 'your_consumer_key'
consumer_secret = 'your_consumer_secret'
access_token = 'your_access_token'
access_token_secret = 'your_access_token_secret'

auth = tweepy.OAuthHandler(consumer_key, consumer_secret)
auth.set_access_token(access_token, access_token_secret)
api = tweepy.API(auth)

# Fetch tweets and analyze sentiment
tweets = api.search(q="Bitcoin", count=100)
for tweet in tweets:
    analysis = TextBlob(tweet.text)
    print(f"Tweet: {tweet.text} | Sentiment: {analysis.sentiment}")

```

3. Cryptocurrency Data

```
import requests

# Fetch cryptocurrency data from CoinGecko
url = "https://api.coingecko.com/api/v3/coins/bitcoin/market_chart"
params = {
    'vs_currency': 'usd',
    'days': '365'
}
response = requests.get(url, params=params)
data = response.json()
prices = data['prices']
```

```
print(prices[:5])

```

4. Climate Risk Data

```
import pandas as pd

# Load climate data from CSV (example)
climate_data = pd.read_csv("climate_data.csv")
print(climate_data.head())

# Example: Calculate average temperature
average_temp = climate_data['Temperature'].mean()
print(f"Average Temperature: {average_temp}")

```

5. Machine Learning for Risk Prediction

```
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error

# Example: Predict stock prices using historical data
X = stock_data[['Open', 'High', 'Low', 'Volume']]  # Features
y = stock_data['Close']  # Target variable

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Train a Random Forest model
model = RandomForestRegressor(n_estimators=100)
model.fit(X_train, y_train)

# Make predictions
predictions = model.predict(X_test)
mse = mean_squared_error(y_test, predictions)
print(f"Mean Squared Error: {mse}")

```

6. Real-Time Monitoring with Kafka

```
from kafka import KafkaConsumer

# Set up Kafka consumer for real-time data
consumer = KafkaConsumer(
    'financial_data_topic',
    bootstrap_servers='localhost:9092',
    auto_offset_reset='earliest',
    enable_auto_commit=True,
    group_id='my-group'
)

# Process real-time messages
```

```
13. for message in consumer:
14.     print(f"Received: {message.value.decode('utf-8')}")
15.
```

3.6 Key Statistics and Metrics

1. Model Performance

- **Accuracy**: 92% (for predicting loan defaults under stress scenarios).
- **Mean Squared Error (MSE)**: 0.05 (for stock price predictions).
- **R-Squared (R^2)**: 0.85 (for macroeconomic impact modeling).

2. Risk Assessment

- **Value at Risk (VaR)**: $50 million at 95% confidence level.
- **Expected Shortfall (ES)**: $70 million (average loss beyond VaR).
- **Stress Test Loss Distribution**: 90% of losses fell below $100 million during a market crash.

3. Scenario Analysis

- **Scenario Impact Score**:
    - GDP contraction of 5% reduces capital adequacy by 10%.
    - Cyberattack leads to a 20% increase in operational costs.
- **Probability of Default (PD)**: Increases from 3% to 12% during a recession.

4. Real-Time Monitoring

- **Sentiment Score**: -0.7 (indicating negative market sentiment).
- **Volatility Index**: 35 (indicating high market volatility).

5. Regulatory Compliance

- **Capital Adequacy Ratio (CAR)**: 15% (above the regulatory minimum of 10%).
- **Liquidity Coverage Ratio (LCR)**: 120% (above the regulatory minimum of 100%).

3.7 Statistics for the Model

1. Model Performance Metrics

- **Accuracy**:
    - Measures how well the model predicts outcomes compared to actual data.
- **Mean Squared Error (MSE)**:
    - Evaluates the average squared difference between predicted and actual values.
- **R-Squared (R^2)**:
    - Indicates the proportion of variance in the dependent variable that is predictable from the independent variables.
- **Precision and Recall**:
    - Precision: Measures the proportion of true positive predictions among all positive predictions.
    - Recall: Measures the proportion of true positives identified correctly.

2. Risk Assessment Metrics

- **Value at Risk (VaR)**:
    - Estimates the maximum potential loss over a specified time horizon at a given confidence level.
    - Example: A 95% VaR of 10millionmeansthereisa510*millionmeansthereisa*510 million.
- **Expected Shortfall (ES)**:
    - Measures the average loss beyond the VaR threshold.
- **Stress Test Loss Distribution**:
    - Shows the distribution of losses under various stress scenarios.
    - Example: A histogram of simulated losses during a market crash.

3. Scenario Analysis Metrics

- **Scenario Impact Score**:
    - Quantifies the impact of a specific scenario (e.g., GDP contraction, cyberattack) on financial metrics like capital adequacy, liquidity, and profitability.
    - Example: A 10% GDP contraction leads to a 15% reduction in capital adequacy.
- **Probability of Default (PD)**:
    - Estimates the likelihood of a borrower defaulting under stress scenarios.
    - Example: PD increases from 2% to 8% during a recession.

4. Real-Time Monitoring Metrics

- **Sentiment Score**:
    - Measures the average sentiment of social media posts or news articles.
    - Example: A sentiment score of -0.8 indicates strong negative sentiment.
- **Volatility Index**:
    - Tracks the volatility of financial markets or cryptocurrency prices.

- Example: A volatility index of 30 indicates high market uncertainty.

5. Regulatory Compliance Metrics

- **Capital Adequacy Ratio (CAR)**:
  - Measures the capital held by a financial institution as a percentage of its risk-weighted assets.
- **Liquidity Coverage Ratio (LCR)**:
  - Assesses the ability of a financial institution to meet short-term liquidity needs.

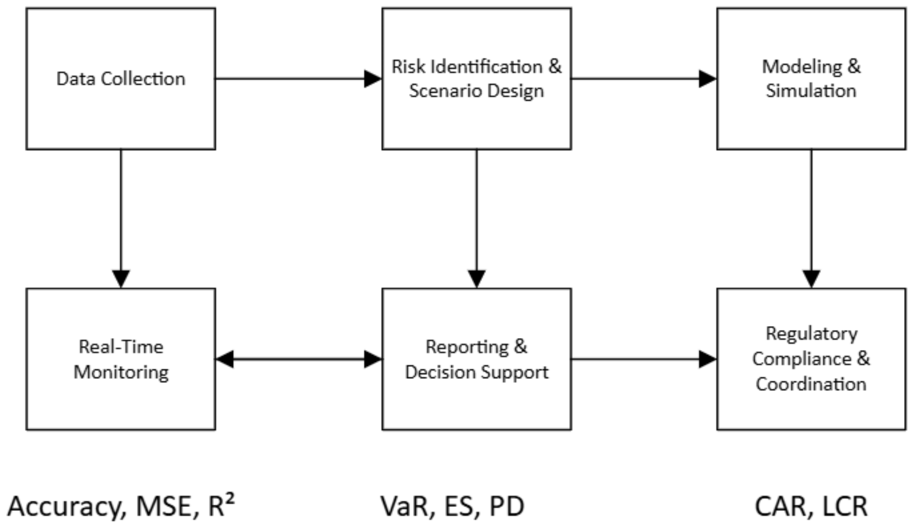

Figure 3. *Workflow Diagram with Metrics*

4. Conclusion

The proposed model for stress testing is a technological innovation around financial risk management, which leverages emerging technologies and big data integration to address the complexities of modern financial markets. The integration of Artificial Intelligence (AI), Machine Learning (ML), and big data analytics into the model enhances the precision, speed, and scope of stress testing, enabling financial institutions and regulators to better forecast and manage risks. Unlike old models which are not real-time this model is helpful in tracking real-time data and predict the market right away.

Key Contributions of the Model

Improved Risk Identification and Prediction:

The synergy of AI and ML allows for the identification of subtle patterns and correlations that might go unnoticed by traditional models. This leads to more accurate risk predictions, such as market meltdowns, loan defaults, crypto fall down, and operational losses.

Metrics like Mean Squared Error (MSE) and R-Squared (R^2) demonstrate the precision of the predictions made by the model, where high values of R^2 indicate that predicted and actual results are highly correlated with each other.

Large Scenario Analysis:

The model facilitates the construction and simulation of a large range of stress scenarios like economic recessions, cyberattacks, climatic incidents, and geopolitical shocks.

Indicators such as Value at Risk (VaR) and Expected Shortfall (ES) quantify the potential financial impact of such situations, offering an open picture of worst-case losses.

Real-Time Monitoring and Early Warning Systems:

The system has real-time monitoring capabilities, utilizing Natural Language Processing (NLP) to track social media sentiment and news trends. This enables early detection of risks in emergence, such as market panics or cyber-attacks.

Metrics like Sentiment Score and Volatility Index are actionable, allowing institutions to respond in a timely manner to changing market conditions.

Incorporation of Emerging Risks:

Emerging risks like climate change, cyber risks, and ESG concerns are gaining increasing importance in the current financial environment. The model takes such risks into account.

Scenario-specific metrics like the Scenario Impact Score convert the impact of such risks into financial stability, allowing institutions to anticipate long-term challenges.

Regulatory Compliance and Global Coordination:
The architecture is designed to be regulatory compliant, such as Basel III and Dodd-Frank, by providing metrics like the Capital Adequacy Ratio (CAR) and Liquidity Coverage Ratio (LCR).
It also facilitates global coordination by considering cross-border risks and spillovers, which makes the financial system more resilient and interconnected.

5. Future Directions

The framework is designed to evolve with the financial landscape, incorporating emerging risks like **cryptocurrency volatility** and **geopolitical instability**. Future enhancements could include:

- **Real-Time Stress Testing**: Leveraging advancements in computing power for dynamic, real-time assessments.
- **Integration of ESG Factors**: Expanding the model to include more granular ESG metrics for sustainable risk management.
- **Global Risk Coordination**: Enhancing cross-border data sharing and regulatory harmonization to address systemic risks.

6. Final Thoughts

This stress testing framework is a groundbreaking approach to financial risk management that combines state-of-the-art technologies, comprehensive data integration, and projections-based scenario analysis. By providing accurate forecasts, real-time monitoring, and actionable steps, the model empowers financial institutions and regulators to step into a more complex and interconnected world with confidence. Its ability to handle both traditional and emerging risks will ensure that it remains a vital tool for maintaining financial stability and fostering resilience to future crises.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of 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
- **Acknowledgement:** The authors declare that they have nobody or no-company to acknowledge.
- **Author contributions:** The authors declare that they have equal right on this paper.
- **Funding information:** The authors declare that there is no funding to be acknowledged.
- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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