Deep learning for economic transformation: a parametric review

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ABSTRACT

Deep learning (DL) is increasingly recognized for its effectiveness in analyzing and forecasting complex economic systems, particularly in the context of Pakistan's evolving economy. This paper investigates DL's transformative role in managing and interpreting increasing volumes of intricate economic data, leading to more nuanced insights. DL models show a marked improvement in predictive accuracy and depth over traditional methods across various economic domains and policymaking scenarios. Applications include demand forecasting, risk evaluation, market trend analysis, and resource allocation optimization. These processes utilize extensive datasets and advanced algorithms to identify patterns those traditional methods cannot detect. Nonetheless, DL's broader application in economic research faces challenges like limited data availability, complexity of economic interactions, interpretability of model outputs, and significant computational power requirements. The paper outlines strategies to overcome these barriers, such as enhancing model interpretability, employing federated learning for better data privacy, and integrating behavioral and social economic theories. It concludes by stressing the importance of targeted research and ethical considerations in maximizing DL's impact on economic insights and innovation, particularly in Pakistan and globally.

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1. INTRODUCTION

Deep learning (DL), a specialized branch of machine learning in artificial intelligence (AI), has experienced rapid growth due to its proficiency in modeling intricate, hierarchical patterns in data. Through the use of multi-layered neural networks [1], DL excels in automatic feature extraction and transformation for a variety of data types, including unstructured data common in real-world applications. The enhancements in hardware and algorithmic innovations, particularly graphics processing units (GPUs), Tensor processing units (TPUs), backpropagation, dropout, and rectified linear units (ReLU), have reduced training times and resources, enabling DL to redefine standards across tasks like computer vision and natural language processing (NLP). This capability to efficiently process high-dimensional, complex data structures has made DL a revolutionary tool in these fields.

In the economic domain, the era of big data is characterized by an exponential increase in data volume and variety, offering both challenges and opportunities [2]. DL has become a critical tool in interpreting this surge of economic data, unveiling patterns that traditional econometric models may miss. Its applications span a wide range of economic subfields, enhancing tasks like demand forecasting, financial risk management, policy analysis, and macroeconomic forecasting [3]. However, the integration of DL in economic research comes with challenges such as model interpretability, data quality, and ethical considerations. Yet, the promise of deeper, more nuanced insights into economic behaviors and outcomes through DL is driving the field towards a more dynamic and precise era of economic analysis.

The evolution of DL has introduced revolutionary architectures like convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformers, each markedly enhancing data analysis capabilities [4]. These models, pivotal in economic analysis and policy forecasting, offer advanced prediction and classification. They come with significant challenges such as interpretability, extensive data requirements, and overfitting risks [5]. Despite these hurdles, continuous advancements in explainable AI (XAI) and DL methodologies are enhancing the robustness and transparency of these models, which is vital for both computer science and economic practitioners. Concurrently, the profound impact of DL in managing and interpreting the vast influx of economic data represents a paradigm shift in the field. Its adeptness at learning hierarchical representations and extracting meaningful features from raw data adeptly navigates the complex and often non-linear patterns in economic data. This capability transforms the challenges posed by big data into opportunities for innovative analysis and more accurate forecasting, thereby steering the field of economics into a new era marked by data-driven and precise understandings of complex dynamics, fundamentally revolutionizing economic analysis and policymaking.

In exploring the integration of DL within economics, this paper casts a wide net, encompassing a diverse array of sub-disciplines such as financial economics, behavioral economics, and macroeconomic forecasting [6]. Each of these areas presents unique applications where DL can unveil intricate patterns and predictive insights, thereby enhancing the accuracy and depth of economic analysis. Our review methodology is meticulously structured, beginning with a thorough literature survey, followed by an analysis of case studies and empirical research that highlight the practical applications of DL in economics. This approach ensures a comprehensive understanding of the current landscape and potential future directions. The expected outcome of this review is twofold: firstly, to provide a clear, detailed overview of how DL is currently being applied in various economic fields, and secondly, to identify gaps and opportunities for future research. This paper aims to serve as a valuable resource for academics and practitioners alike, offering insights that could shape future economic research and policymaking. By bridging the gap between complex computational techniques and economic analysis, it is anticipated that this review will not only advance the field of economics but also inspire innovative applications of DL that could have a significant impact on economic theory and practice.

This review paper progresses with an exploration of the fundamentals of DL, investigating into its core algorithms and theoretical underpinnings. It then progresses to examine the applications of DL in various sectors of Pakistan's economy, highlighting its transformative potential. The paper also addresses challenges and limitations in the implementation of these technologies. In its conclusion, it synthesizes these insights, emphasizing DL.

2. DEEP LEARNING FUNDAMENTALS

DL principles are foundational in advancing various fields, including the economy, through hierarchical feature learning via deep neural networks (DNNs) [7]. These networks, including CNN, RNNs, attention mechanisms, and graph neural networks (GNNs), enable nuanced data interpretation and analysis [8]. Learning algorithms evolve with methods like contrastive learning and meta-learning, optimizing model efficiency through techniques like Lookahead and cyclical learning rates [9]. DL also emphasizes end-to-end learning for direct raw data processing, supported by generative models like variational autoencoders (VAEs) and generative adversarial networks (GANs) for complex data handling [10]. Model evaluation considers robustness, fairness, and uncertainty estimation, introducing methods for adversarial training and fairness algorithms [11]. Interpretability challenges are being addressed through advanced techniques like counterfactual explanations and causal inference models, ensuring decisions are understandable and justifiable [12].

3. DL APPLICATIONS IN RESOLVING ECONOMIC CHALLENGES OF PAKISTAN

DL has emerged as a transformative force in various sectors of Pakistan's economy, addressing unique challenges through state-of-the-art algorithms and technologies. In Islamic economics, DL applications dependent upon deep belief networks (DBNs) and autoencoders have revolutionized zakat management and Islamic banking, enhancing financial stability and compliance with Sharia [13]. The agriculture and rural development sector has seen advancements with CNNs for crop health monitoring and long short term memory (LSTM) networks for market trend forecasting, significantly aiding in poverty reduction and resource management [14]. Education and human capital development benefit from gradient boosting machines for labor market analysis, aligning educational programs with employment needs [15]. Climate change initiatives leverage supervised learning for environmental policy modeling [16], while infrastructure development utilizes deep reinforcement learning to enhance project efficiency [17]. Microfinance and small business development use support vector machines (SVMs) for credit risk assessment, fostering entrepreneurship [18]. Social protection strategies employ cluster analysis and decision trees to optimize social insurance programs [19]. Governance and institutional reform benefit from sentiment analysis in NLP for transparency and corruption detection [20]. Herewith, regional integration and trade analyses leverage time series forecasting for strategic trade expansion [21], showcasing DL's pivotal role in economic advancement and policy formulation across Pakistan.

3.1. Challenges and opportunities

The integration of DL in Pakistan's economic sectors presents both significant challenges and opportunities. Data availability and quality, crucial for DL model training, are hindered by inconsistencies and limited access, necessitating data standardization and comprehensive collection efforts. Model transparency and interpretability issues challenge policymaking applications, driving the need for XAI frameworks to demystify complex DL decisions [22]. Ethical considerations and algorithmic bias raise concerns over fairness, prompting the adoption of bias detection and mitigation strategies for responsible AI deployment [23]. Institutional adaptation and policy development are essential for ethical AI [24] use and fostering collaboration across academia, industry, and government to enhance economic research and policy analysis.

Thereby, DL's progression demands addressing technological bottlenecks like memory requirements, distributed computing challenges, and energy consumption, alongside the development of scalable, sustainable solutions tailored to developing economies like Pakistan. Innovations in automated machine learning (AutoML) [25] and continual learning models, model compression for deployment on resource-limited devices, robustness against data distribution shifts, and effective multi-modal data integration are pivotal for maximizing DL's impact. For that reason, optimal DL model performance necessitates co-designing hardware [26] and software, highlighting the intricate balance between technological advancements and practical applications in economic contexts. All the preceding and succeeding data is context based on following envisioned environment, as illustrated in Table 1.

Table 1. Optimal DL environment and infrastructure for big data analysis in economics

Component	Specification	Reasoning/benefit
	Hardware	
CPU	Intel Xeon or AMD EPYC with high core counts (e.g., 32-64 cores)	Provides robust multi-threading capabilities for data preprocessing and model training.
GPU	NVIDIA Tesla V100 or A100, or AMD Radeon Instinct MI100	Offers substantial parallel processing power necessary for accelerated model training and inference.
RAM	256 GB-1 TB DDR4 or DDR5	Facilitates large-scale data loading and in-memory computations, essential for big data analysis.
Storage	NVMe SSDs in TBs for fast read/write; additional HDD for archival storage	Ensures quick data access and storage scalability for voluminous datasets.
	Software	
Operating system	Linux (e.g., Ubuntu 20.04 LTS or CentOS)	Widely supported by DL and big data tools, offering stability and performance.
DL framework	TensorFlow 2.x, PyTorch, or Keras	Supports advanced DL model development with extensive libraries and community support.
Data processing	Apache Spark, Hadoop	Efficient for handling and processing large-scale data, integrating well with ML and DL libraries.
GPU Acceleration	CUDA, cuDNN	Optimizes GPU performance for DL tasks, crucial for model training and inference.
Visualization	TensorBoard, Matplotlib	Enables monitoring of model training and provides tools for data visualization.
	Datasets	
Public datasets	World Bank Open Data, IMF Financial Data, Penn World Table, Global Financial Data, Human Development Index (HDI), Consumer Price Index (CPI), Purchasing Power Parity (PPP) datasets, Panel Study of Income Dynamics (PSID), University of Michigan Consumer Sentiment Index, OECD.Stat, Federal Reserve Economic Data (FRED), Bureau of Labor Statistics Data, Eurostat, United Nations Comtrade Database, Zillow Real Estate Data.	Provides a rich variety of data for model training and benchmarking in respective fields.
Proprietary data	Organizational or collaboration-specific datasets, adhering to ethical and legal guidelines	Ensures relevant and specialized data for specific research needs and domains.
Synthetic data	Tools like GANs or simulation software for generating synthetic data	Useful for scenarios with data limitations or privacy concerns, augmenting real data or creating new scenarios.

3.2. Hypothesis support/contradiction

Presented research critically evaluates how empirical evidence and theoretical insights align with or counter our hypotheses regarding DL impact on Pakistan's economic sectors. While findings largely affirm our hypothesis, highlighting DL's role in boosting sectoral efficiency, decision-making, and innovation, challenges in data access, infrastructure, and skills training suggest hurdles in DL's seamless integration. These findings offer a realistic view of DL adoption in Pakistan, pointing to crucial areas for targeted research, policy action, and skill development to fully realize DL's capabilities. This concise analysis provides a clear picture of DL's potential benefits and the obstacles to its implementation, underscoring the need for a strategic approach in leveraging DL for economic progress.

4. DEMYSTIFICATION OF THE REVIEW PROCESS

In our exhaustive review of DL applications in economics, we carried out a detailed comparative analysis of current methodologies. This included a comprehensive assessment of advanced DL architectures such as GANs, CNNs, RNNs, and transformers, particularly in their application to crucial economic sectors like market prediction, risk assessment, and policy analysis. Our benchmarking of these DL models against conventional econometric methods utilized sophisticated metrics like the area under the curve (AUC) [27], mean absolute error (MAE) [28], and economics-specific measures such as economic value added (EVA). This analysis not only underscored the areas where DL models excel, as shown in Table 2, but also pinpointed realms where traditional methods remain effective. Herewith, a keen emphasis on vector error correction (VEC) models are indispensable in econometrics for analyzing cointegrated time series, vital for both short-term and long-term macroeconomic analysis. The unique ability of VEC models to correct deviations from long-term equilibrium positions them as crucial tools for understanding the dynamic adjustment processes in economics. Especially in Pakistan, where economic variables often demonstrate long-term equilibrium relationships (e.g., between GDP, inflation, and interest rates), VEC models are invaluable for policymakers and researchers in forecasting and evaluating economic policies efficiently.

Table 2. Comparative analysis of DL model and traditional econometric method performance across various criteria

Evaluation criteria	DL model performance	Traditional econometric method performance	Metrics used	Context/remarks
Predictive accuracy	High	Moderate	AUC, MAE	DL models like CNNs and LSTMs show superior accuracy in complex data pattern recognition and forecasting.
Complexity handling	Excellent	Poor	Computational time, model complexity	Complex DL architectures, such as transformers, adeptly handle high-dimensional, non-linear data.
Interpretability	Low	High	Qualitative analysis, LIME, SHAP	Traditional methods, like linear regression, outperform DL in terms of model transparency and understandability.
Data efficiency	Moderate	Highs	Data utilization ratio	DL techniques, especially in unsupervised learning like autoencoders, are less efficient with smaller datasets compared to traditional econometrics.
Real-time Processing	Good	Varies	Processing speed, latency	Real-time processing capabilities of RNNs and CNNs surpass most traditional methods, depending on specific use cases.
Scalability	High	Moderate	Scalability metrics	DL models, particularly those using parallel processing like GANs, are more scalable to larger datasets.
Economic impact	Varies	Varies	EVA, cost-benefit analysis	Both DL models, like neural networks for market prediction, and traditional methods, like time-series analysis, have varied impacts depending on the economic application.
Generalizability	Moderate	High	Cross-validation scores	Traditional methods like ARIMA models often show better generalizability across different datasets compared to specific DL models like CNNs.
Robustness	Moderate	High	Adversarial testing, stability checks, sensitivity analysis, noise resistance testing, outlier detection, model stress testing	Traditional econometric methods are typically more robust to outliers and anomalies compared to DL models like deep feedforward networks.
Implementation cost	High	Low	Cost analysis, computational resources	Implementing DL models such as GANs and complex neural networks often incurs higher computational and expertise costs.

We systematically revealed significant knowledge gaps and emerging research areas in the economic domain, particularly in segments like behavioral economics where the potential of DL remains largely untapped. We identified specific challenges in data availability within lesser-explored sectors and regions, marking new frontiers for DL in economics. Concurrently, we developed a set of standardized evaluation metrics and best practices for DL applications in economics, focusing on accuracy, fairness, robustness, and economic impact to ensure a thorough and objective assessment of DL models. Emphasizing the importance of interdisciplinary collaboration and ethical data sharing, our review advocates for strong partnerships between computer scientists, economists, and policymakers. This synergy, coupled with a commitment to open-source data and research sharing, paves the way for accelerated DL innovation and its practical application in the economic sphere. Aligning technological advancements with economic and societal values, this collaborative approach is detailed in the Table 3, which outlines the gaps, research areas, and collaborative strategies, underscoring the unique challenges and opportunities in each area and reinforcing the role of collaborative efforts in the progressive application of DL in economics.

A structured framework tailored to the economic domain is detailed in Table 4 through the taxonomy of DL models, encompassing a spectrum from supervised to unsupervised learning approaches. This classification addresses the multifaceted requirements of economic data analysis, including diverse model architectures for specific tasks like time series forecasting, NLP, and anomaly detection. By offering a comprehensive approach, it ensures a holistic strategy for investigating economic datasets, enabling nuanced analysis and informed decision-making across various areas of economic research.

Table 3. DL applications in economics (knowledge gaps, research areas, and collaborative framework)

Knowledge gaps and emerging research areas	DL Potential	Data challenges	Evaluation metrics and best practices	Interdisciplinary collaboration and ethical data sharing
Behavioral economics	Untapped	Limited studies and datasets available	Accuracy, fairness, robustness, economic impact	Collaboration among computer scientists, economists, policymakers; advocacy for open-source data
Informal economy analysis	High	Lack of comprehensive and structured data	Data preprocessing standards, model generalizability	Cross-sector data sharing agreements, ethical data usage guidelines
Microfinance and small business Development	Moderate	Sparse data on micro-level economic activities	Predictive performance, scalability	Joint projects between academia and financial institutions, data privacy considerations
Environmental economics	Growing	Need for region-specific environmental data	Sustainability metrics, long-term impact evaluation	Partnerships with environmental agencies, responsible data handling
Resource allocation in developing countries	Emerging	Inadequate data in low-resource settings	Resource efficiency, cost-effectiveness	Collaborations with local governments and NGOs, culturally sensitive data practices
Digital currency and blockchain economics	Expanding	Variability and novelty of data sources	Security measures, transaction accuracy	Global data sharing initiatives, adherence to international regulatory standards
Labor market dynamics and automation	Significant	Dynamic and evolving workforce data	Labor market impact, skill gap analysis	Multi-disciplinary research consortia, workforce data protection
International trade and market integration	High	Cross-border trade data complexities	Trade efficiency, market prediction accuracy	Inter-governmental data agreements, trade data standardization efforts
health economics and policy	Moderate	Health data privacy and heterogeneity	Health outcome prediction, policy impact assessment	Health sector collaborations, stringent data security protocols
Urban and regional planning	Growing	Urban data diversity and scale	Urban development metrics, infrastructure impact	Smart city initiatives, public-private data partnerships

4.1. Supervised learning models

In the of Pakistan's economic landscape, supervised learning [29] DL models are adeptly utilized for predictive modeling in sectors like finance and agriculture. These models, trained on historical economic data, excel in forecasting market trends, agricultural yields, and consumer behavior, providing vital insights for policy-making and strategic economic planning. Their ability to handle large-scale, complex datasets and discern intricate patterns makes them indispensable tools for driving data-driven economic policies and initiatives.

Table 4. Economics application focused DL model taxonomy

DL models	
Supervised learning models	CNNs
	RNNs
	LSTMs
	GRUs
	Feedforward neural networks
	SVMs
	Decision trees
Unsupervised learning models	Autoencoders
	(DBNs
	GANs
	Self-organizing maps
	Restricted Boltzmann machines (RBMs)
Semi-supervised learning models	GNNs
	VAEs
Reinforcement learning models	Deep Q-networks (DQNs)
	Policy gradient methods
	Actor-critic methods
Hybrid models	Convolutional recurrent neural networks (CRNN)
	Encoder-decoder architectures
Transfer learning models	Pretrained CNNs (e.g., ResNet, Inception)
	Pretrained language models (e.g., BERT, GPT)
Time series and forecasting models	ARIMA with neural networks
	Sequence-to-sequence (Seq2Seq) models
Natural language processing models	transformers
	Attention mechanisms
Anomaly detection models	One-class SVMs
	Isolation forests
Optimization and regularization techniques	Dropout
	Batch normalization
	Adam optimizer
	L1/L2 regularization

4.1.1. Convolutional neural networks

CNNs, designed for grid-like data analysis such as images, excel in recognizing spatial features through convolution operations [30]. They automate the learning of feature hierarchies, crucial for tasks like image classification and segmentation. Challenges include the need for extensive labeled data, high computational resources, and hyperparameter tuning. In economic contexts, CNNs analyze spatial data like satellite imagery to understand land use and productivity [31]. Despite their power, CNNs' complexity and 'black-box' nature raise interpretability and ethical concerns, emphasizing the need for transparency and bias mitigation in their deployment [32].

4.1.2. Recurrent neural networks

RNNs excel in processing sequential data, a match for economic systems' dynamic nature, particularly in sectors like agriculture and finance within Pakistan [33]. These networks capture temporal patterns in data, aiding in forecasts and financial analysis. RNNs face challenges like the vanishing gradient problem, addressed by advances in LSTM and GRU technologies, enhancing their capability to remember information over extended periods [34]. Despite computational demands, RNNs' unique architecture makes them invaluable for economic research and policymaking, offering insights into temporal economic dynamics.

4.1.3. Long short-term memory networks

LSTMs enhance RNN capabilities, addressing long-term dependency challenges in economic data analysis. Through specialized gates and cell states, they regulate information flow, maintaining relevant data while discarding the unnecessary [35]. Optimization techniques and hyperparameter tuning ensure model stability and prevent overfitting. LSTMs are adept at processing complex temporal sequences, making them invaluable for forecasting and analyzing economic trends, significantly outperforming traditional models in areas like inflation forecasting and stock market analysis, thus offering a dynamic tool for economic decision-making [36].

4.1.4. Gated recurrent units

GRUs, a streamlined variant of RNNs, are equipped with update and reset gates to efficiently manage sequential data, crucial in economic modeling [37]. These mechanisms allow GRUs to maintain or discard information from previous states, making them adept at capturing long-term dependencies in economic time series like GDP and inflation rates. Offering a simpler architecture than LSTMs, GRUs are highly effective in economic forecasting, financial analysis, and policy evaluation, providing a flexible tool for integrating historical and real-time data to generate insightful economic predictions.

4.1.5. Feedforward neural networks

Feedforward neural networks, optimized for economic data analysis, play a crucial role with their configurable hidden layers and neurons to handle complex relationships in economic variables. Utilizing non-linear activation functions like ReLU and tanh, these networks adeptly model the dynamics prevalent in economic data. Regularization techniques are employed to prevent overfitting, ensuring models are generalizable and robust. The networks undergo training with specific cost functions and optimization algorithms tailored for economic tasks, with pre-processing steps ensuring data integrity and relevance. Evaluation employs metrics and visualization techniques for insightful analysis and interpretation, enhancing the networks' applicability to economic forecasting and analysis [38].

4.1.6. Support vector machines

SVMs are critical in economic data analysis, with kernel selection like linear, polynomial, and RBF crucial for model performance [39]. These kernels enable SVMs to model complex, non-linear economic relationships. Optimization methods and feature engineering tailored to economic contexts enhance SVMs' effectiveness. Interpretable machine learning techniques, such as LIME and SHAP, provide insights into model predictions, crucial for economic policymaking [40]. SVMs' adaptability to multi-class and multi-label problems makes them invaluable for addressing varied economic challenges such as poverty classification or sector-specific risk prediction.

4.1.7. Decision trees

In economic analysis, decision tree models excel by incorporating domain-specific features, such as poverty indicators and economic trends, tailored to the Pakistani economy's unique aspects. Techniques like principal component analysis (PCA) and recursive feature elimination (RFE) refine these models by reducing dimensionality and selecting relevant features, enhancing accuracy and economic sensibility. Advanced algorithms like XGBoost and ensemble methods improve prediction through aggregated tree results, while regularization curbs overfitting. Decision trees' interpretability is enhanced through techniques like LIME, offering insights into economic scenarios and potential policy impacts, making them vital for robust economic forecasting and policy analysis [41].

4.2. Unsupervised learning models

Unsupervised learning models [42] are pivotal for uncovering hidden patterns and relationships in unlabeled economic data. These models excel at clustering and dimensionality reduction, enabling the discovery of intrinsic structures in complex datasets like consumer spending patterns or market segmentations. Their ability to learn efficient representations without explicit supervision makes them invaluable for identifying underlying economic trends and anomalies, thereby informing targeted policy decisions and economic strategies.

4.2.1. Autoencoders

Autoencoders play a pivotal role in economic data analysis, with VAEs [43] enhancing anomaly detection and convolutional autoencoders (CAEs) extracting spatial features relevant to economic activities. Recurrent autoencoders (RAEs) [44] adeptly handle temporal economic data, capturing dynamic trends in key indicators like GDP and inflation rates. Advanced applications include generating synthetic economic scenarios with conditional VAEs and employing deep GANs for fraud detection. Furthermore, sparsity-inducing autoencoders streamline variable selection, while transfer learning boosts forecasting accuracy. Integrating XAI methods [45] ensures model transparency, vital for economic policymaking [46].

4.2.2. Deep belief networks

Unsupervised feature learning particularly with DBNs [47] and stacked RBMs, offers transformative potential in dissecting intricate economic datasets like monetary aggregates, stock prices, and trade data. These architectures excel in layer-wise, unsupervised extraction of features, progressively building a deeper understanding of the data. Techniques like contrastive divergence or persistent contrastive divergence are employed to efficiently train individual RBMs and DBMs, enhancing their ability to capture the hierarchical representation of economic features. This hierarchical structure is key in unraveling complex relationships and temporal dynamics inherent in economic data, providing a more nuanced understanding than traditional linear models.

The architecture and design of these models are tailored to specific economic tasks. The number of layers and hidden units in RBM/DBM structures are optimized based on the requirements of the task at hand, be it forecasting, anomaly detection, or sentiment analysis from economic news. The connection patterns between layers, whether directed or undirected, are chosen to best capture the specific economic dependencies under study. Regularization techniques, such as L1/L2 penalties and weight decay, are crucial in preventing overfitting, particularly pertinent given the often limited and noisy economic data in Pakistan. When integrated with supervised learning, these pre-trained DBN features can be fine-tuned for tasks like economic forecasting, credit risk assessment, or policy impact analysis, providing a more robust framework than traditional econometric methods like autoregressive integrated moving average (ARIMA) or vector autoregression (VAR) models. Ensemble learning approaches when combining DBNs with other DL models like CNNs or LSTMs exhibited enhance performance on specific economic applications, leveraging the strengths of different architectures.

Nevertheless, during our analysis, we have found following shortcomings and limitations:

a) Limited availability of high-quality, labeled economic data in Pakistan for effective training.
b) Substantial computational resources required for training deep unsupervised models.
c) Challenges in the explainability and interpretability of DBN-based models in economic decision-making.
d) Need for model adaptation to cater to unique economic features of Pakistan, such as its informal sector and financial system dynamics.
e) Potential overfitting risks due to complex model architectures and noisy real-world economic data.

4.2.3. Generative adversarial networks

GANs [48] revolutionize economic data analysis with their generator and discriminator architectures, employing deep CNNs (DCNNs) for data generation and PatchGAN [49] for intricate pattern discernment. Innovations like wasserstein GAN (WGAN) [50] improve stability, while conditional GANs tailor outputs to specific economic scenarios. Training employs advanced loss functions and optimization techniques for better convergence. In Pakistan focused economic applications, GANs are eligible to demonstrate their utility in a range of scenarios. For synthetic high-frequency data generation, GANs are adept at filling gaps in datasets or simulating high-frequency economic data points, enhancing econometric analysis and aiding in policy evaluation and risk assessment. In financial market prediction, their ability to model complex time series data facilitates accurate market trend predictions and anomaly detection. GANs also contribute significantly to economic agent simulation, where they model realistic behaviors of economic agents and their interactions, crucial for market analysis and understanding the dynamics of economic systems. These capabilities are particularly useful in forecasting responses to economic shocks, offering valuable insights for economists and policymakers in crafting responsive and informed economic strategies.

4.2.4. Self-organizing maps

The architecture of self-organizing maps (SOMs) [51] is fundamentally shaped by the design of the Kohonen layer, where the selection of grid topology, such as a 2D hexagonal or toroidal structure, is critical. This choice significantly affects the map's proficiency in encapsulating and representing intricate economic relationships, thereby determining the effectiveness of SOMs in economic data analysis. Map unit activation functions, like Gaussian, and distance metrics [52], such as Euclidean or cosine, are critical in determining how input features activate map units. For input vector construction, effective feature selection and preprocessing methods are essential, especially given the varied nature of Pakistani economic data. Techniques like normalization and scaling are employed to standardize the input data, ensuring consistent treatment across diverse economic indicators. Weight vector initialization strategies, ranging from random to pre-trained initializations, significantly impact the SOM's convergence and the formation of a meaningful topographic map, which is essential for interpreting complex economic datasets.

The training of SOMs involves a competitive learning algorithm, where a winner-take-all learning mechanism is employed. The selection of an appropriate neighborhood function, such as bubble or Mexican hat, along with annealing schedules for the learning rate and neighborhood radius, is crucial in guiding the self-organization process. Visualization and interpretation techniques, including U-matrix and component planes, are employed to visualize the topographic maps, providing insights into the clustering of economic data. Quantifying cluster quality through metrics like quantization error aids in assessing the map's effectiveness in capturing economic patterns. Evaluation and validation of the SOM model involve techniques like hold-out sets and cross-validation, with metrics specifically tailored to economic applications, such as clustering accuracy and relevance to economic indicators ensure the model's robustness and applicability.

Advanced SOM variants, such as growing hierarchical SOM and fuzzy SOM, offer potential benefits in economic research, particularly in handling hierarchical structures or uncertainty in economic

data. Incorporating Pakistani economic dataset into the SOM architecture or training process can further enhance the model's relevance and effectiveness. However, the model does have limitations:
a) Susceptibility to the curse of dimensionality in high-dimensional economic datasets.
b) Challenges in determining the optimal number of neurons and topology for specific economic tasks.
c) Limited interpretability in complex economic scenarios due to abstract nature of topographic maps.
d) Dependency on initial weight vector settings and learning parameters, impacting model stability.
e) Computational complexity in large-scale applications, requiring significant processing resources.

4.2.5. Restricted Boltzmann machines

RBMs [53] are critical in learning economic features, with architecture and training methods influencing their effectiveness in analyzing complex economic data. Alternative activation functions and learning algorithms enhance their ability to model intricate relationships, such as income inequality. Weight initialization and optimization techniques are key to RBM performance [54], addressing the nuances of economic datasets. Visualization and feature importance analysis provide insights into economic significance, while transfer learning and domain knowledge integration ensure models are attuned to local economic contexts, enhancing their applicability in economic analysis and policymaking. Designing RBM architectures that incorporate domain knowledge about economic relationships or Pakistani economic scenarios ensures that the models are tailored to local needs. Ensuring model explainability and building trust in their economic applications is achieved through techniques like attention mechanisms or layer-wise relevance propagation. These approaches not only offer insights into the RBM's predictions but also enhance their credibility and reliability in economic policymaking and analysis.

4.3. Semi-supervised learning models

Semi-supervised learning DL models [55] are instrumental for integrating limited labeled data with abundant unlabeled data, enhancing predictive accuracy in tasks like market segmentation and consumer behavior analysis. These models effectively bridge the gap between supervised and unsupervised learning by leveraging the structure within economic datasets to infer missing labels, crucial for robust economic forecasting and policy evaluation in data-scarce environments. Their ability to utilize unlabeled data for training makes them particularly valuable in scenarios where acquiring fully labeled economic datasets is challenging or cost prohibitive.

4.3.1. Graph neural networks

GNNs [56] are essential in analyzing economic networks, with node and edge embeddings capturing the intricate properties and temporal dynamics within these networks. Techniques like graph convolutional networks (GCNs) and graph attention networks (GATs) [57] facilitate mapping nodes into high-dimensional spaces, preserving structural and feature-related information. GNN architectures leverage message passing schemes, pooling, and readout layers for graph-level predictions, employing task-specific loss functions for training in semi-supervised settings. Scalability and efficiency are addressed through mini-batch training and approximate message passing, enabling GNNs to manage large, complex economic networks effectively.

Some of the prominent observed limitations and shortcomings of GNNs are:
a) Handling of large-scale graphs can be computationally intensive, requiring significant resources.
b) Over-smoothing in deep GNN layers can lead to loss of local structure information.
c) Model interpretability remains a challenge, particularly in understanding how GNNs arrive at specific predictions.
d) Adapting GNNs to dynamic graphs with changing structures over time can be complex.
e) Integrating heterogeneous data sources into a unified graph representation requires careful preprocessing and feature engineering.

4.3.2. Variational autoencoders

VAEs are adept at handling the complexity of diverse economic data (such as, consumer purchase data, stock market data, economic indicators, price elasticity data, financial time series data, supply chain data, banking transaction data, real estate market data, consumer credit data, international trade data), employing a variational inference framework to approximate latent variable distributions. Their architecture [58], incorporating CNNs or RNNs, excels in processing time series, textual, or image data. VAEs feature a latent space that captures essential economic features, facilitating nuanced data reconstruction or generation. Training leverages techniques like stochastic gradient descent with optimizers for complex representation learning, while advancements such as conditional VAEs and ensemble learning enhance accuracy, interpretability, and model performance in economic analysis [59].

Our investigation revealed that the VAEs face several limitations, including the complexity of tuning hyperparameters to achieve a balance between reconstruction quality and latent space regularization. They can generate unrealistic synthetic data if not properly regularized or trained. Understanding the latent space and its representations poses another challenge. Training VAEs on large, high-dimensional datasets is computationally intensive, and their performance heavily depends on the quality and volume of training data, affecting their generalizability and reliability.

4.4. Reinforcement learning models

Reinforcement learning (RL) models [60] are emerging as powerful tools for optimizing decision-making processes in areas like resource allocation, market simulation, and financial portfolio management. These models iteratively learn optimal strategies by interacting with an economic environment, using reward signals to guide decisions, which is crucial for adapting to the dynamic and often uncertain economic scenarios. The technical complexity of these models lies in balancing exploration and exploitation to maximize long-term rewards, a challenging task that requires sophisticated algorithms and careful tuning to the specific economic context.

4.4.1. Deep Q-networks

DQNs are instrumental in navigating Pakistan's complex economic landscape, requiring sophisticated state representation to incorporate key economic indicators and policy nuances. Feature engineering, state discretization, and handling partial observability are essential for adapting raw economic data to RL models. The design of action spaces and reward functions is crucial, focusing on economic policy decisions and aligning model objectives with national economic goals [61]. Training DQNs [62] involves advanced techniques like experience replay and prioritized experience replay, with meticulous hyperparameter tuning to optimize performance for economic applications.

Our analysis has uncovered the following, prominent, but not limited to, drawbacks and constraints associated with the DQN model:

a) High-dimensional state space requires extensive computational resources.
b) Difficulty in accurately modelling the complex, dynamic nature of economic systems.
c) Overfitting risk due to the complexity and richness of economic data.
d) Challenges in designing appropriate reward functions that accurately reflect long-term economic objectives.
e) Limited availability of comprehensive and reliable economic data for training and validation.

4.4.2. Policy gradient methods

Developing policy gradient models [63] for economic analysis involves choosing the right policy function parameterization, from simple linear models to complex neural networks. Techniques like REINFORCE or proximal policy optimization (PPO) cater to specific economic scenarios (e.g., dynamic pricing, supply chain optimization, portfolio management, and resource allocation), with exploration strategies like epsilon-greedy ensuring a balance between exploiting known rewards and exploring new possibilities. Optimization includes careful discount factor selection and reward shaping to align models with economic objectives (e.g., replay and batching). Experience replays and data preprocessing from diverse sources enrich model training, while evaluation metrics assess policy stability and dynamic economic impact.

Despite their advantages, policy gradient methods in economic modeling come with inherent limitations. The complexity of accurately modeling and predicting economic outcomes necessitates extensive computational resources and a deep understanding of both machine learning and economics. The reliance on substantial and diverse data sources for training can be a challenge, especially in scenarios with limited or noisy data. Also, ensuring the interpretability and explainability of these models is crucial, as economic policy decisions based on these models can have far-reaching consequences. The trade-off between model complexity and interpretability remains a key consideration in their deployment for economic analysis and policymaking.

4.4.3. Actor-critic methods

Actor-critic methods integrate policy (actor) and value (critic) functions to guide economic decision-making, utilizing advanced neural networks for precise action selection and evaluation [64]. Techniques like deep deterministic policy gradients (DDPG) [65] and recurrent actor-critic networks (RAC) capture the complexities of economic dynamics, while multi-agent actor-critic (MAAC) models [66] address interactions within decentralized economic systems. These DL methods are instrumental in shaping rewards to achieve long-term economic objectives, employing strategies to ensure model stability and efficiency. Despite challenges in computational demands and data quality, actor-critic models offer valuable insights into economic policy and strategy effectiveness, highlighting their importance in economic simulations (e.g., double Q-learning and trust region policy optimization (TRPO) [67]) and policymaking.

The implementation of actor-critic models, while offering substantial benefits, is not without its challenges, particularly in the field of economic simulations. These models demand significant computational resources, especially when applied to large-scale economic scenarios. Accurately capturing the diverse and dynamic characteristics of economic systems adds another layer of complexity. Designing and shaping rewards that effectively mirror long-term economic objectives is a nuanced task, requiring careful consideration. Furthermore, the effectiveness of these models heavily relies on the quality and accessibility of economic data, which is critical for their training and validation. A key challenge lies in striking the right balance between the complexity of the models and their interpretability, a crucial aspect in the ambit of economic policymaking.

4.5. Hybrid models

Hybrid DL models [68] integrate diverse neural network architectures like CNNs for spatial data analysis and RNNs for temporal data processing. Are increasingly being deployed for comprehensive economic forecasting and analysis. These models leverage the strengths of different learning paradigms-convolutional layers for extracting spatial features from economic data like geographical patterns, and recurrent layers for modeling time-dependent phenomena such as stock market trends or GDP growth, providing a multifaceted approach to economic data analysis that is both robust and adaptable to the complex and dynamic nature of economy.

4.5.1. Convolutional recurrent neural networks

CRNNs [69] are an innovative class of hybrid DL models that merge the spatial feature extraction capabilities of CNNs with the temporal data processing prowess of RNNs. In the convolutional layers, CRNNs utilize 1D convolutions for feature extraction from time-series economic data like GDP, inflation, and unemployment rates. They employ multi-scale feature extraction techniques, including dilated convolutions, to capture both long-term trends and short-term fluctuations in economic indicators. Spatial convolutions are also integral for analyzing geographical dependencies within economic data, aiding in understanding regional income disparities and other spatial economic phenomena. Residual connections in these layers facilitate better gradient flow, significantly enhancing the training performance of these models.

The recurrent layers in CRNNs, often comprising LSTM units or GRUs, are adept at capturing the temporal dynamics within economic datasets. Bi-directional LSTMs extend this capability by processing information from both past and future contexts, enabling predictions of economic growth based on historical trends and anticipated policy changes. Attention mechanisms are incorporated to selectively focus on specific parts of the time series that are most relevant for the prediction task, such as pinpointing key economic events that have significant impacts on certain sectors. In terms of hybrid architectures, the combination of CNNs and RNNs varies, with CNN-LSTM models being particularly effective in simultaneously extracting spatial and temporal features. Encoder-decoder architectures leverage CNNs for encoding complex economic data and RNNs for decoding it into forecasts or predictions. Optimization and regularization of these CRNN models involve adaptive learning rate algorithms for efficient training, dropout layers to combat overfitting, and early stopping strategies to maintain model robustness. Evaluation metrics for CRNNs range from MSE or MAE for regression tasks like economic growth prediction, to R-squared or F1-score for classification tasks such as predicting loan defaults or assessing the risk of economic recessions. Visualizing the model's predictions and residuals is also crucial for analyzing its behavior and identifying any potential biases in its forecasts.

4.5.2. Encoder-decoder architectures

Encoder-decoder architectures in DL, such as RNNs, CNNs, and transformers, are pivotal for economic data analysis, translating complex datasets into actionable insights. These models excel in time series forecasting, sentiment analysis, and policy simulation by incorporating attention mechanisms and domain-specific knowledge. Despite their versatility, challenges include data quality reliance, interpretability, and computational demands, underscoring the need for advanced data processing and model optimization strategies [70]. Hence, applied models are instrumental in economic forecasting and policy analysis, effectively incorporating exogenous factors and leveraging text and sentiment analysis for market trend predictions. Despite their utility in anomaly detection and model simulations, challenges such as data quality, interpretability, and computational demands limit their effectiveness, highlighting the need for improved data processing and model optimization strategies.

4.6. Transfer learning models

Transfer learning approach [71] allows for leveraging learned patterns and features from one economic domain and applying them to another. Significantly reducing the need for extensive data and computational resources, which are often constraints in economic research. This methodology is particularly beneficial for complex tasks like economic forecasting, market trend analysis, and policy impact assessment, where it can enhance model performance and accelerate the training process by adapting previously learned knowledge to the specific nuances of Pakistan's economy.

4.6.1. Pretrained CNNs (e.g., ResNet, Inception)

Pretrained CNNs [72] like ResNet, Inception, and EfficientNet, trained on diverse datasets, offer extensive feature learning for economic data analysis, adapting through transfer learning or fine-tuning based on dataset size, computational resources, and task specificity. Adapting to Pakistani economic contexts involves adjustments in layer training and domain-specific data augmentation to enhance model performance and generalizability. Optimizing these models requires careful hyperparameter tuning and selection of appropriate loss functions to ensure accuracy and relevance in economic applications, from microfinance to agricultural analysis.

Our analysis has uncovered a range of limitations in the use of these models, which include, but are not limited to, the following challenges:

a) Potential for pretrained models to carry biases from the original training data, affecting their applicability to national economic contexts.
b) Overfitting risks due to complex model architectures when applied to smaller or less diverse local datasets.
c) Challenges in interpreting the features and layers of deep pretrained CNNs, impacting model transparency.
d) Computational and resource requirements for fine-tuning and optimizing large pretrained models.

4.6.2. Pretrained language models (e.g., BERT, GPT)

Pretrained language models (PLMs) [73] like BERT and GPT, utilizing transformer encoder-decoder architectures, are revolutionizing natural language processing with their ability to understand and generate language from extensive training on text corpora. These models' adaptability to economic data, through fine-tuning with domain-specific content and employing techniques like few-shot learning, enables sophisticated economic analysis tasks. However, technical challenges such as computational demands, the need for explainability, bias mitigation, and the development of specialized models like FinBERT or multilingual capabilities for diverse Pakistani languages present significant considerations for effective application in economic research [74].

Our investigation has identified a spectrum of limitations in the application of these models, encompassing a variety of challenges. These include, but are not restricted to, the following areas of concern:

a) Challenges in fine-tuning PLMs to specific economic contexts due to limited domain-specific training data.
b) High computational demands for training and adapting large-scale language models.
c) Risks of perpetuating existing biases from pre-trained datasets into economic analysis.
d) Difficulties in ensuring the interpretability and transparency of complex PLM architectures.
e) Potential for overfitting on limited or niche economic data samples, affecting the generalizability of model insights.

4.7. Time series and forecasting models

DL models specialized in time series and forecasting [75], such as LSTM and GRU models, are being increasingly utilized to predict key economic indicators like GDP growth, inflation rates, and market trends. These models excel in handling sequential data by learning temporal dependencies and patterns, crucial for accurate economic forecasting in a country marked by fluctuating market conditions and economic policies. Their technical sophistication lies in effectively capturing both short-term fluctuations and long-term trends in economic data, which is essential for robust policy-making and economic planning in Pakistan.

4.7.1. ARIMA with neural networks

The hybrid ARIMA [76] with neural networks model, including variations like ARIMA-RNNs and ARIMA-CNNs, merges traditional ARIMA's trend and seasonality handling with neural networks' ability to capture nonlinear patterns and complex data features. This approach enhances time series prediction accuracy, with specific applications in economic forecasting, such as foreign exchange rates, stock market indices, and inflation rates. Despite its advantages, challenges include complex integration, substantial computational demands, model interpretability, and reliance on extensive historical data for training, necessitating careful design and optimization.

4.7.2. Sequence-to-sequence models

Seq2Seq models [77], particularly relevant for time series data, are pivotal in analyzing and forecasting economic trends. These models typically employ RNNs like LSTM and GRU, as well as Transformer models, which are adept at capturing temporal dependencies in economic data. The inclusion of attention mechanisms, such as those developed by Bahdanau and Luong, significantly enhances the model's ability to learn long-range dependencies, a crucial feature for understanding complex economic sequences like financial time series and policy narratives. Hybrid architectures like convolutional LSTMs offer a robust solution for handling mixed data modalities, including text and numerical data, commonly encountered in Pakistani economic studies.

Adapting Seq2Seq models for forecasting macroeconomic indicators such as inflation and GDP involves incorporating exogenous factors like global events and policy shocks. These models are also leveraged for policy analysis, generating comprehensive economic reports, and summarizing economic news in a manner that's tailored to the pre-defined context. They prove invaluable in textual tasks like sentiment analysis of economic discourse, news summarization of significant economic events, and automatic classification of economic documents. Advanced techniques in Seq2Seq models, including beam search and teacher forcing, are employed to enhance the quality of inferences drawn from the model. However, these Seq2Seq models do face challenges, particularly in economic applications. Issues such as data scarcity can hinder the model's training and effectiveness. Furthermore, the complexity inherent in Seq2Seq models often leads to interpretability issues, making it challenging to understand and explain the model's predictions and outputs in an economic context. These limitations underscore the need for continued innovation and adaptation in the use of Seq2Seq models within the field of economics.

4.8. Natural language processing models

DL models for NLP [78], such as transformer-based architectures are increasingly employed for analyzing economic texts, including policy documents, market reports, and social media discourse. These models excel in understanding and generating complex language structures, enabling sophisticated tasks such as sentiment analysis, topic extraction, and automated summarization, which are crucial for real-time economic decision-making and market trend analysis. Their technical efficacy lies in the ability to process large volumes of unstructured text data and extract relevant economic insights, aiding policymakers and analysts in comprehending the multifaceted economic narrative of Pakistan.

4.8.1. Transformers

The NLP transformers model [79], integrating self-attention mechanisms, excels in analyzing economic data, including Urdu language texts through UrduBERT [80], and financial contexts with FinBERT. It supports diverse applications from policy analysis to consumer behavior prediction across Pakistan's linguistic landscape, utilizing domain-specific fine-tuning and multilingual capabilities. Challenges include limited localized data, addressed through data augmentation and multi-modal learning, enhancing the interpretability and application breadth of transformers in economic analysis.

4.8.2. Attention mechanisms

The NLP attention mechanisms [81], particularly within transformer-based architectures like BERT and RoBERTa, have revolutionized the analysis of complex economic texts by capturing intricate dependencies. These mechanisms, through self-attention and multi-head attention, allow for nuanced understanding and interpretation of economic data, enhancing tasks like sentiment analysis and forecasting. Hybrid models combining attention mechanisms with econometric approaches offer sophisticated analytical tools. Despite challenges like data scarcity and model interpretability, advancements in data pre-processing, attention visualization, and specialized embeddings promise deeper economic insights.

4.9. Anomaly detection models

Autoencoders and GANs as DL models [82] for anomaly detection are gaining prominence for their ability to spot irregularities and fraudulent patterns in financial transactions and market data. These models are highly adept at understanding the standard patterns within complex economic datasets and identifying anomalies, playing a key role in the early detection of fraud and market anomalies. Their effectiveness is rooted in their capacity to analyze extensive data sets, decipher complex data structures, and pinpoint outliers with precision. This capability is vital for preserving financial integrity and ensuring the stability of an expanding economy. Table 5 provides a structured approach to understanding and managing various types of anomalies that can occur in economic systems, with a focus on how DL models can be utilized for identification and subsequent management strategies.

Table 5. DL models for anomaly detection and management in economic applications

Sample: anomaly type	Sample: potential causes	Sample: anomaly identification (DL models)	Anomaly management strategies
Financial fraud	Unusual transaction patterns, identity theft	Autoencoders, one-class SVMs	Real-time monitoring, transaction verification protocols
Market manipulation	Artificial inflation/deflation of asset values	LSTM networks, GANs	Regulatory oversight, market surveillance systems
Economic data discrepancies	Reporting errors, data tampering	CNNs for pattern recognition, RNNs	Data validation checks, cross-verification with alternative sources
Consumer behavior shifts	Socioeconomic changes, market trends	NLP transformers for sentiment analysis	Adaptive marketing strategies, consumer engagement surveys
Policy impact anomalies	Unintended consequences of new policies	Transformer-based models for policy analysis	Policy revision and adjustment, Stakeholder feedback integration
Supply chain disruptions	Natural disasters, geopolitical events	CNNs for image data analysis (satellite imagery)	Contingency planning, diversified supply sources

4.9.1. One-class SVMs

One-class SVMs [83], particularly effective in anomaly detection within economic data, leverage specific kernels (such as radial basis function (RBF) or polynomial (Poly)), and domain-specific feature engineering to enhance detection accuracy. Integrating DL architectures further improves anomaly discernment. The optimization process involves fine-tuning parameters and developing robust scoring mechanisms, with explainability addressed through interpretative techniques. Despite their effectiveness in various economic applications, challenges like handling imbalanced datasets and ensuring interpretability in complex scenarios remain, highlighting the importance of expert domain knowledge for their application.

4.9.2. Isolation forests

Isolation forests [84] offer a unique approach to anomaly detection in economic datasets through the use of isolation trees, distinguishing themselves from conventional models by isolating outliers. This method is particularly suited to economic data due to its ability to handle high dimensionality with advanced variants like patch forests. The technique involves calculating path length scores to identify anomalies, with visualization aids for interpretation. Despite its computational efficiency and adaptability to sparse data, challenges in explainability and concept drift remain, driving research towards more interpretable and adaptive models for economic analysis.

4.10. Optimization and regularization techniques

In economic data analysis using DL, optimization and regularization techniques like Adam optimizer, L1/L2 regularization, and dropout are crucial for enhancing model performance and preventing overfitting. These techniques optimize the training process of neural networks, ensuring robust and generalizable models suited for complex economic forecasting and analysis tasks. Their application is vital in efficiently handling high-dimensional economic data, balancing model complexity with prediction accuracy, and ensuring the models' resilience against the variability inherent in dynamic economic framework.

4.10.1. Dropout

Dropout [85], a technique for mitigating overfitting in neural networks, selectively deactivates neurons during training, introducing randomness that promotes model robustness. It enhances feature selection, prevents neuron co-adaptation, and works alongside or outperforms traditional regularization methods. Optimizing dropout involves adjusting parameters for different network layers, with applications in economic forecasting, policy analysis, and credit risk assessment. Despite its benefits, challenges include determining the optimal dropout rate and ensuring model consistency. Future developments may focus on adaptive dropout techniques and integrating dropout with advanced regularization for improved economic model performance.

4.10.2. Batch normalization

Batch normalization addresses the issue of internal covariate shift, which is particularly pertinent in economic data analysis [86]. Covariate shift, arising from factors such as seasonality or policy changes, can significantly affect the training of DL models. Batch normalization addresses this by normalizing the activations within mini-batches, thereby stabilizing the learning dynamics and enhancing model performance.

This normalization proves crucial in economic datasets where covariate shift is prominent, ensuring consistent performance across varied data distributions. For instance, in tasks involving macroeconomic data analysis, where seasonality and policy shifts are common, Batch normalization helps in maintaining model stability and improving predictive accuracy.

The technique also plays a vital role in mitigating the challenges of vanishing or exploding gradients, particularly in complex economic models like LSTM networks used for macroeconomic forecasting. By normalizing activations, batch normalization contributes to smoother gradient propagation, leading to faster convergence during training. This not only reduces training time but also enhances the efficiency of resource utilization, a significant advantage when dealing with large-scale economic datasets. Besides, it introduces learnable parameters (γ, β) that allow the model to adapt to varying data distributions, an essential feature for dynamic economic modeling where data characteristics evolve over time, such as in financial market analyses. This adaptability makes batch normalization preferable compared to other normalization techniques in dynamic economic tasks. Furthermore, the regularization effect of batch normalization reduces the model's sensitivity to weight initializations, promoting better generalization to unseen economic data and yielding more robust predictions.

Recent advancements in batch normalization, like GroupNorm, LayerNorm, and spectral normalization, open new avenues for specific economic applications. These advanced techniques hold potential in areas like credit risk assessment or financial time series analysis, enhancing the model's ability to handle complex economic phenomena. Despite its many benefits, batch normalization has its limitations, such as dependency on mini-batch size and potential reduction in training stability under certain conditions. As per our investigation, we envision that the field is likely to witness the emergence of advanced normalization methods capable of accommodating a broader spectrum of economic data scenarios. Such developments would offer greater adaptability and resilience in DL applications, significantly enhancing their utility in economic analysis and forecasting.

4.10.3. Adam optimizer

The Adam optimizer is renowned for its effectiveness in handling sparse gradients on noisy problems, a common challenge in economic data analysis. In the context of economic data, particularly that representing various Pakistani economic phenomena like inflation, exchange rate, and GDP, the tuning of Adam's hyperparameters–including the initial learning rate, beta1, beta2, and epsilon–plays a crucial role in determining model performance and convergence speed. Adaptive learning rate schedules, such as warm-up and decay phases, are particularly beneficial for dealing with the non-stationary features or volatile periods frequently observed in national economic data. Nevertheless, despite its advantages, Adam optimizer has limitations, particularly in scenarios where a fine balance between exploration and exploitation of the solution space is required. Its efficacy can be influenced by the choice of hyperparameters, and improper settings may lead to suboptimal convergence. We envision that in future researchers should focus on developing more adaptive and intuitive variants of Adam that can automatically adjust their parameters based on the characteristics of the economic dataset, enhancing model performance and applicability in diverse economic contexts.

4.10.4. L1/L2 regularization

L1 and L2 regularizations are critical techniques in DL, particularly in the context of economic data analysis, each offering distinct advantages. L1 regularization, also known as Lasso, is adept at producing sparse solutions by setting the coefficients of irrelevant features to zero. This property not only enhances the model's interpretability but also makes it robust to outliers due to its absolute penalty term. Group Lasso variations are particularly useful for economic applications, as they encourage sparsity within grouped features, such as economic sectors, while adaptive Lasso dynamically adjusts the penalty to individual features based on their importance. Proximal gradient descent algorithms are employed as efficient optimization methods for achieving sparse solutions in L1 regularization. On the other hand, L2 Regularization, known as Ridge, is effective in shrinking all coefficients towards zero, thus reducing model complexity and mitigating overfitting. It improves generalization on unseen data and handles multicollinearity by reducing sensitivity to correlated features, thereby stabilizing coefficient estimates. Elastic net regularization combines the benefits of both L1 and L2 penalties, striking a balance between sparsity and coefficient shrinkage. Techniques like early stopping and cross-validation are crucial for optimally tuning regularization hyperparameters, such as lambda, and Bayesian inference methods can incorporate prior information about coefficients through the L2 penalty.

In the settings of economic modeling, the dynamic selection of penalty parameters based on data characteristics or economic theories is vital for prioritizing certain features. Simultaneously optimizing regularization and model parameters can lead to enhanced accuracy. Tailoring these regularization techniques to specific economic problems and data characteristics ensures their relevance and effectiveness in economic analysis. However, a one-size-fits-all approach to regularization can be limiting, as different economic datasets may require different levels of sparsity or shrinkage for optimal performance. Future directions might involve developing more adaptive regularization techniques that can automatically adjust based on the unique characteristics of the economic data being analyzed, leading to more accurate and interpretable economic models.

Table 6 generalizes the characteristics of these models. The actual performance and costs can vary significantly depending on the specific architecture, size of the economic dataset, and computational resources available. For instance, in economics, datasets might have unique features like time series data, complex relationships, or require interpretability for policy decision-making, which can influence the choice and performance of the model.

Table 6. Comparative analysis of DL models in economics across key criteria

DL model type	Performance metrics	Training time	Computational cost	Interpretability
Supervised learning models	High accuracy, precision, recall	Can be extensive for large datasets	High for large, complex models	Low to moderate, depending on model complexity
Unsupervised learning models	Cluster purity, silhouette score	Varies, often quicker than supervised models	Moderate to high, depending on complexity	Low to moderate, as these models can be more abstract
Semi-supervised learning models	Better than unsupervised, but varies	Moderate, leveraging both labeled and unlabeled data	Moderate to high	Low to moderate, depending on the balance of supervised and unsupervised elements
Reinforcement learning models	Reward accumulation, success in task-specific metrics	Often extensive, especially in complex environments	High, due to iterative nature and complexity of environments	Low, as decision-making processes can be complex and non-linear
Hybrid models	Depends on the specific combination of models	Varies, often longer due to combining models	High, combining costs of multiple models	Generally low, increased complexity reduces interpretability
Transfer learning models	High in tasks similar to the base model's training	Shorter, as it builds on pre-trained models	Lower than training from scratch	Low to moderate, depending on the complexity of the base model
Time series and forecasting models	Forecast accuracy, error metrics (e.g., MAE, RMSE)	Can be extensive for long series and complex models	Moderate to high, especially for models handling large time series	Moderate, as time series models can be more interpretable
Natural language processing models	Accuracy, F1 score, BLEU score for translations	Extensive, especially for large language models	Very high for state-of-the-art models	Low, given the complexity of language and model size
Anomaly detection models	Detection accuracy, false alarm rate	Varies, but can be extensive for complex scenarios	Moderate to high, depending on model complexity	Moderate, as these models often have more understandable decision boundaries
Optimization and regularization techniques	Depends on the base model	Can increase training time due to additional constraints	Varies, additional steps can increase computational costs	Can improve interpretability by simplifying models

5. FUTURISTIC QUANTUM COMPUTING AND DEEP LEARNING IN ECONOMICS

Quantum computing's (QCs) [87] potential to revolutionize economic modeling lies in its ability to crack complex optimization problems and uncover hidden patterns in vast datasets. By harnessing the power of qubits and DL algorithms, we can tackle challenges like portfolio optimization, risk management, and efficient resource allocation. Paving the way for a more robust and data-driven economic future.

5.1. Quantum machine learning in economics

Quantum machine learning (QML) algorithms [88] are emerging as powerful tools for solving complex economic problems, harnessing the principles of quantum mechanics to potentially revolutionize how we approach these challenges. For instance:

a) The variational quantum eigensolver (VQE) is one such algorithm, particularly useful in finding the ground state of economic Hamiltonians for optimization problems, such as portfolio allocation in finance.
b) Another notable algorithm, the quantum approximate optimization algorithm (QAOA), is adept at solving combinatorial problems relevant in economics, like resource allocation and network design, by utilizing quadratic objective functions.
c) Quantum support vector machines (qSVM) hold the promise of classifying economic data with enhanced performance, especially in high-dimensional spaces, using quantum kernels.
d) Quantum Boltzmann machines (qBMs) offer a novel approach to model complex economic relationships through unsupervised learning, potentially leading to groundbreaking insights.

e) Hybrid quantum-classical algorithms are also being explored, combining the strengths of quantum computing for specific subtasks with classical computing for the overall framework, thus offering a pragmatic approach to integrating quantum capabilities in economic problem-solving.

5.2. Processing and representing economic data using quantum methodologies

In terms of quantum data processing and representation for economic applications, several quantum techniques stand out. For instance:

a) The quantum fourier transform (QFT) can efficiently analyze economic time series data, uncovering hidden patterns and seasonal trends that might be elusive to classical methods.
b) Quantum phase estimation offers the potential for exponential speedup in estimating parameters of complex economic models compared to classical techniques.
c) Quantum principal component analysis (qPCA) aids in reducing the dimensionality of economic data while retaining crucial information for analysis and prediction.

Moreover, techniques for quantum data encoding, such as amplitude and phase encoding, are pivotal in representing economic data in qubits for processing by quantum algorithms. Error correction and fault tolerance are crucial aspects, given the current challenges of noisy quantum devices, ensuring reliable and accurate quantum computations in economic applications.

5.3. DL focused QC applications

The applications of QC-enhanced DL in economics are vast and promising. For instance:

a) Quantum-assisted recurrent neural networks (qRNNs) could offer unprecedented accuracy in financial market prediction, analyzing market trends, and forecasting asset prices.
b) Quantum risk analysis models could revolutionize economic risk management, particularly in fields like portfolio optimization and insurance pricing.
c) In supply chain management, quantum-powered algorithms could optimize logistics more efficiently than ever before.
d) Simulating economic models on quantum computers could provide a new paradigm in economic policy design, enabling the evaluation of policy impacts before their real-world implementation.
e) Anomaly detection algorithms using quantum Boltzmann machines could be particularly effective in identifying fraudulent activities in economic transactions.

Conversely, the field of quantum computing, especially in economic applications, faces several considerations. The current state of quantum hardware, characterized by error-prone quantum devices, necessitates noise mitigation strategies and often calls for hybrid quantum-classical approaches. The development of quantum algorithms and software tools tailored for economic applications is an ongoing process, marking an emerging field with immense potential. Thus, integrating these advanced quantum algorithms into existing economic frameworks and data pipelines remains a significant challenge, requiring careful consideration to ensure practical and impactful applications.

6. CHALLENGES AND ETHICAL CONSIDERATIONS

As DL models increasingly influence economic analysis, forecasting, and policymaking, it becomes imperative to address the ethical implications and challenges associated with their deployment. Here are some key points highlighting these ethical considerations and challenges (i.e., but not limited to):

a) DL models in economics can inadvertently perpetuate or amplify biases present in the training data, leading to unfair or discriminatory outcomes. Addressing these biases requires careful data curation and implementation of fairness algorithms.
b) Many DL models, particularly those based on complex architectures, are often seen as 'black boxes'. Ensuring transparency and explainability is crucial for trust and accountability, especially in policy-related applications.
c) With DL models often relying on large datasets, including sensitive economic indicators and personal financial data, maintaining data privacy and security is paramount.
d) DL applications in economics must adhere to existing legal and regulatory frameworks, which can be challenging given the fast-paced evolution of AI technologies.
e) The deployment of advanced DL models in economics could potentially widen economic disparities, with benefits accruing more to those with access to high-quality data and computational resources.
f) Over-reliance on DL models might undermine human expertise and judgment in economic decision-making, raising concerns about the autonomy of human decision-makers.
g) The broad societal impact of DL-driven economic decisions, such as those influencing employment or social welfare policies, must be carefully considered to avoid unintended negative consequences.

h) Establishing clear lines of accountability for decisions made by or with the assistance of DL models is essential to address potential errors or harmful outcomes.

7. PROSPECTIVE TRENDS IN DL IMPLEMENTATION WITHIN ECONOMICS

The future of DL implementation is poised to transform both theoretical and applied aspects of the field (i.e., Economics), with significant advancements anticipated across various sub-disciplines. For instance, we envision the following:

a) Forecasting critical economic indicators such as GDP, inflation, and unemployment will see enhanced precision and reliability through DL models, which can process complex, nonlinear data more effectively than traditional methods. DL algorithms are also being developed to analyze and predict economic crises, offering the potential to preemptively identify warning signs and mitigate risks. In policymaking, reinforcement learning models are emerging as powerful tools for simulating the effects of monetary and fiscal policy decisions, enabling policymakers to test scenarios before implementation.
b) In the sphere of microeconomics, DL models are revolutionizing the understanding of consumer behavior and market responses. These models can analyze vast amounts of data to predict how consumers will react to changes in prices, products, and market conditions. DL also enhances the analysis of firm dynamics and competition, offering deeper insights into market structures and strategic interactions.
c) Development economics stands to gain from DL in several ways. DL methods are increasingly used for predicting poverty and inequality, enabling more targeted and effective social programs. DL-based models are aiding in the design and implementation of social interventions, ensuring that resources are allocated where they are most needed. Moreover, DL techniques are being employed to analyze the impact of development policies on economic growth, offering a more nuanced understanding of policy effectiveness. Importantly, DL is playing a crucial role in understanding the economic implications of climate change, a key concern in development economics.
d) Econometrics is also witnessing a DL revolution. Novel DL architectures are being developed for econometric analysis, enhancing the efficiency and accuracy of economic estimations. Unsupervised learning is being explored for its potential in economic data analysis, uncovering hidden patterns and relationships without predefined models. A key challenge being addressed is the interpretability and explainability of DL-based economic models, crucial for their acceptance and understanding in the wider economic community.

Looking ahead, the integration of DL with traditional economic models will be critical. This hybrid approach promises to combine the strengths of both methodologies, offering more robust and comprehensive analyses. The rise of XAI in economics will help demystify complex DL models, making their decisions and predictions more transparent and trustworthy. Ethical considerations, such as data privacy, bias, and the societal impact of automated decision-making, will remain at the forefront, ensuring that DL applications in economics are aligned with societal values and norms. Finally, the role of big data in driving DL applications in economics cannot be overstated; the ability to process and analyze vast datasets will continue to be a key driver of innovation and advancement in the field.

7.1. Future research builds upon review findings

Our review paper lays a comprehensive foundation for future research in several ways, identifying both the transformative potential of DL in economic sectors and the challenges specific to implementing these technologies in Pakistan. Future research can build upon these findings through various avenues:

a) There is a need for empirical research that assesses the impact of DL applications in critical sectors identified within our review, such as agriculture, finance, education, and healthcare. These studies should aim to quantify the economic benefits, efficiency improvements, and social impacts of DL implementations. Such data-driven insights would provide a stronger basis for policy recommendations and investment decisions.
b) Our review highlights challenges like data availability, computational resource constraints, and the skills gap as significant barriers to DL adoption in Pakistan. Future research should focus on developing innovative solutions to these challenges, such as low-resource DL models, data privacy-preserving techniques, and scalable training programs for DL skills development. Experimenting with federated learning in the Pakistani context could be particularly fruitful for overcoming data scarcity and privacy concerns.
c) There is a profound opportunity for cross-disciplinary research that combines economics, computer science, and social sciences to explore the broader implications of DL on Pakistan's economy. Future studies could investigate the socio-economic impacts of DL, such as job displacement and creation, and the ethical considerations of automated decision-making in public and private sectors.

d) Conducting comparative studies between Pakistan and other countries with similar economic backgrounds can provide valuable insights into best practices for DL adoption in developing economies. These analyses can help in understanding the role of governance, infrastructure, and cultural factors in the successful implementation of DL technologies.
e) To truly gauge the impact of DL on economic reform, longitudinal studies that track the progress of DL implementations over time are crucial. These studies can provide real-world evidence of the sustainability and long-term benefits of DL applications in various economic sectors.
f) Our review suggests that certain sectors such as small and medium enterprises (SMEs), informal economy, and regional trade can significantly benefit from DL technologies. Future experiments should aim to uncover the specific DL tools and models that can be most effective in these areas, addressing unique challenges and opportunities.

8. CONCLUSION

This review paper has systematically examined the burgeoning role of DL in catalyzing economic reform within Pakistan, showcasing its pivotal contributions across diverse sectors including finance, healthcare, agriculture, and urban development. The evidence marshalled illustrates DL's profound capacity to streamline processes, enhance predictive accuracy, and facilitate informed decision-making, thus heralding a new era of economic efficiency and innovation. However, the adoption of DL in Pakistan faces notable challenges such as limited data accessibility, infrastructural constraints, and a prevailing skills gap, which collectively impede the full realization of DL's potential. Addressing these hurdles necessitates a concerted effort towards improving data collection and processing frameworks, upgrading technological infrastructure, and investing in skill development programs tailored to DL competencies. Future directions for DL research in Pakistan should focus on developing localized DL models that are robust to data scarcity and adaptable to the unique socio-economic contexts of the country. Furthermore, interdisciplinary collaborations that bridge the gap between technology and policy-making can further harness DL's transformative power, driving sustainable economic growth and positioning Pakistan at the forefront of the global digital economy. This paper emphasizes the critical need for continued exploration and investment in DL technologies, advocating for a strategic approach to overcoming current limitations and unlocking the vast potential of DL for economic advancement.

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REFERENCES

[1] M. Alshayeji, J. Al-Buloushi, A. Ashkanani, and S. Abed, "Enhanced brain tumor classification using an optimized multi-layered convolutional neural network architecture," *Multimedia Tools and Applications*, vol. 80, no. 19, pp. 28897–28917, Jun. 2021, doi: 10.1007/s11042-021-10927-8.
[2] C. Acciarini, F. Cappa, P. Boccardelli, and R. Oriani, "How can organizations leverage big data to innovate their business models? A systematic literature review," *Technovation*, vol. 123, p. 102713, May 2023, doi: 10.1016/j.technovation.2023.102713.
[3] L. Chen, M. Pelger, and J. Zhu, "Deep learning in asset pricing," *Management Science*, vol. 70, no. 1, pp. 1–75, Feb. 2023, doi: 10.1287/mnsc.2023.4695.
[4] K. Olorunnimbe and H. Viktor, "Deep learning in the stock market-a systematic survey of practice, backtesting, and applications," *Artificial Intelligence Review*, vol. 56, no. 3, pp. 2057–2109, Jun. 2022, doi: 10.1007/s10462-022-10226-0.
[5] S. E. Whang, Y. Roh, H. Song, and J.-G. Lee, "Data collection and quality challenges in deep learning: a data-centric AI perspective," *The VLDB Journal*, vol. 32, no. 4, pp. 791–813, Jan. 2023, doi: 10.1007/s00778-022-00775-9.
[6] Y. Song, X. Tang, H. Wang, and Z. Ma, "Volatility forecasting for stock market incorporating macroeconomic variables based on GARCH-MIDAS and deep learning models," *Journal of Forecasting*, vol. 42, no. 1, pp. 51–59, Aug. 2022, doi: 10.1002/for.2899.
[7] I. Chronopoulos, A. Raftapostolos, and G. Kapetanios, "Forecasting value-at-risk using deep neural network quantile regression," *Journal of Financial Econometrics*, vol. 22, no. 1, pp. 1–34, May 2023, doi: 10.1093/jjfinec/nbad014.
[8] A. Lazcano, P. J. Herrera, and M. Monge, "A combined model based on recurrent neural networks and graph convolutional networks for financial time series forecasting," *Mathematics*, vol. 11, no. 1, pp. 1–21, Jan. 2023, doi: 10.3390/math11010224.
[9] S. Mukherjee, B. Sadhukhan, N. Sarkar, D. Roy, and S. De, "Stock market prediction using deep learning algorithms," *CAAI Transactions on Intelligence Technology*, vol. 8, no. 1, pp. 82–94, Aug. 2021, doi: 10.1049/cit2.12059.
[10] J. Jordon *et al.*, "Synthetic data - what, why and how?," *Royal Society*, vol. 34, pp. 1–57, May 2022, doi: 10.48550/arXiv.2205.03257.
[11] M. M. Moein *et al.*, "Predictive models for concrete properties using machine learning and deep learning approaches: a review," *Journal of Building Engineering*, vol. 63, p. 105444, Jan. 2023, doi: 10.1016/j.jobe.2022.105444.
[12] D. Singh, "Foreign direct investment and local interpretable model-agnostic explanations: a rational framework for FDI decision making," *Journal of Economics, Finance and Administrative Science*, vol. 28, Nov. 2023, doi: 10.1108/jefas-05-2021-0069.
[13] M. Bineid, N. Beloff, M. White, and A. Khanina, "CADM: big data to limit creative accounting in saudi-listed companies," *18th Conference on Computer Science and Intelligence Systems (FedCSIS), Warsaw, Poland,* vol. 2023, Sep. 2023, pp. 103–110, doi: 10.15439/2023f3888.

[14] E. Saralioglu and O. Gungor, "Semantic segmentation of land cover from high resolution multispectral satellite images by spectral-spatial convolutional neural network," *Geocarto International*, vol. 37, no. 2, pp. 657–677, Mar. 2020, doi: 10.1080/10106049.2020.1734871.
[15] M. G. Celbiş, "Unemployment in rural Europe: a machine learning perspective," *Applied Spatial Analysis and Policy*, vol. 16, no. 3, pp. 1071–1095, Jun. 2022, doi: 10.1007/s12061-022-09464-0.
[16] M. Pichler and F. Hartig, "Machine learning and deep learning-a review for ecologists," *Methods in Ecology and Evolution*, vol. 14, no. 4, pp. 994–1016, Feb. 2023, doi: 10.1111/2041-210x.14061.
[17] T. Gao *et al.*, "A deep reinforcement learning approach to mountain railway alignment optimization," *Computer-Aided Civil and Infrastructure Engineering*, vol. 37, no. 1, pp. 73–92, May 2021, doi: 10.1111/mice.12694.
[18] S. G. Fashoto, B. A. Akinnuwesi, E. Mbunge, and A. S. Metfula, "Financial inclusion dataset classification in Eswatini using support vector machine and logistic regression," *International Journal of Business Information Systems*, vol. 43, no. 4, pp. 507–527, 2023, doi: 10.1504/ijbis.2023.132811.
[19] A. López-Vargas, A. Ledezma-Espino, and A. Sanchis-de-Miguel, "Methods, data sources and applications of the artificial intelligence in the energy poverty context: a review," *Energy and Buildings*, vol. 268, p. 112233, Aug. 2022, doi: 10.1016/j.enbuild.2022.112233.
[20] S. Verma, "Sentiment analysis of public services for smart society: literature review and future research directions," *Government Information Quarterly*, vol. 39, no. 3, p. 101708, Jul. 2022, doi: 10.1016/j.giq.2022.101708.
[21] A. Uroos, M. S. Shabbir, M. U. Zahid, G. Yahya, and B. A. Abbasi, "Economic analysis of corruption: evidence from Pakistan," *Transnational Corporations Review*, vol. 14, no. 1, pp. 46–61, May 2021, doi: 10.1080/19186444.2021.1917331.
[22] X. Li *et al.*, "Interpretable deep learning: interpretation, interpretability, trustworthiness, and beyond," *Knowledge and Information Systems*, vol. 64, no. 12, pp. 3197–3234, Sep. 2022, doi: 10.1007/s10115-022-01756-8.
[23] D. K. Nguyen, G. Sermpinis, and C. Stasinakis, "Big data, artificial intelligence and machine learning: a transformative symbiosis in favour of financial technology," *European Financial Management*, vol. 29, no. 2, pp. 517–548, May 2022, doi: 10.1111/eufm.12365.
[24] J. Brusseau, "AI human impact: toward a model for ethical investing in AI-intensive companies," *Journal of Sustainable Finance and Investment*, vol. 13, no. 2, pp. 1030–1057, Jan. 2021, doi: 10.1080/20430795.2021.1874212.
[25] M. Schmitt, "Automated machine learning: AI-driven decision making in business analytics," *Intelligent Systems with Applications*, vol. 18, p. 200188, May 2023, doi: 10.1016/j.iswa.2023.200188.
[26] P. Dhilleswararao, S. Boppu, M. S. Manikandan, and L. R. Cenkeramaddi, "Efficient hardware architectures for accelerating deep neural networks: survey," *IEEE Access*, vol. 10, pp. 131788–131828, 2022, doi: 10.1109/access.2022.3229767.
[27] P. A. Jaskowiak, I. G. Costa, and R. J. G. B. Campello, "The area under the ROC curve as a measure of clustering quality," *Data Mining and Knowledge Discovery*, vol. 36, no. 3, pp. 1219–1245, Apr. 2022, doi: 10.1007/s10618-022-00829-0.
[28] T. O. Hodson, "Root-mean-square error (RMSE) or mean absolute error (MAE): when to use them or not," *Geoscientific Model Development*, vol. 15, no. 14, pp. 5481–5487, Jul. 2022, doi: 10.5194/gmd-15-5481-2022.
[29] R. Liu and C. S. Pun, "Machine-Learning-enhanced systemic risk measure: a two-step supervised learning approach," *Journal of Banking and Finance*, vol. 136, p. 106416, Mar. 2022, doi: 10.1016/j.jbankfin.2022.106416.
[30] S. Tuo *et al.*, "A regional industrial economic forecasting model based on a deep convolutional neural network and big data," *Sustainability*, vol. 13, no. 22, pp. 1–11, Nov. 2021, doi: 10.3390/su132212789.
[31] L. Zhang, Z. Huang, W. Liu, Z. Guo, and Z. Zhang, "Weather radar echo prediction method based on convolution neural network and long short-term memory networks for sustainable e-agriculture," *Journal of Cleaner Production*, vol. 298, p. 126776, May 2021, doi: 10.1016/j.jclepro.2021.126776.
[32] M. Krichen, "Convolutional neural networks: a survey," *Computers*, vol. 12, no. 8, p. 151, Jul. 2023, doi: 10.3390/computers12080151.
[33] Y.-L. Wang, H. Jahanshahi, S. Bekiros, F. Bezzina, Y.-M. Chu, and A. A. Aly, "Deep recurrent neural networks with finite-time terminal sliding mode control for a chaotic fractional-order financial system with market confidence," *Chaos, Solitons and Fractals*, vol. 146, p. 110881, May 2021, doi: 10.1016/j.chaos.2021.110881.
[34] G. Li, P. Yang, C. Qian, R. Hong, and K. Tang, "Stage-wise magnitude-based pruning for recurrent neural networks," *IEEE Transactions on Neural Networks and Learning Systems*, pp. 1–15, 2022, doi: 10.1109/tnnls.2022.3184730.
[35] D. Hopp, "Economic nowcasting with long short-term memory artificial neural networks (LSTM)," *Journal of Official Statistics*, vol. 38, no. 3, pp. 847–873, Sep. 2022, doi: 10.2478/jos-2022-0037.
[36] R. Jaiswal, G. K. Jha, R. R. Kumar, and K. Choudhary, "Deep long short-term memory based model for agricultural price forecasting," *Neural Computing and Applications*, vol. 34, no. 6, pp. 4661–4676, Nov. 2021, doi: 10.1007/s00521-021-06621-3.
[37] H. Hamzah, S. Winardi, P. E. E. Chrismawan, and R. Tambunan, "Robust stock price prediction using gated recurrent unit (GRU)," *International Journal of Informatics and Computation*, vol. 5, no. 1, pp. 1–10, Sep. 2023, doi: 10.35842/ijicom.v5i1.56.
[38] V. Novykov, C. Bilson, A. Gepp, G. Harris, and B. J. Vanstone, "Empirical validation of ELM trained neural networks for financial modelling," *Neural Computing and Applications*, vol. 35, no. 2, pp. 1581–1605, Oct. 2022, doi: 10.1007/s00521-022-07792-3.
[39] S. Benítez-Peña, R. Blanquero, E. Carrizosa, and P. Ramírez-Cobo, "Cost-sensitive probabilistic predictions for support vector machines," *European Journal of Operational Research*, vol. 314, no. 1, pp. 268–279, Apr. 2024, doi: 10.1016/j.ejor.2023.09.027.
[40] Y. Nohara, K. Matsumoto, H. Soejima, and N. Nakashima, "Explanation of machine learning models using shapley additive explanation and application for real data in hospital," *Computer Methods and Programs in Biomedicine*, vol. 214, p. 106584, Feb. 2022, doi: 10.1016/j.cmpb.2021.106584.
[41] H. Qian, B. Wang, M. Yuan, S. Gao, and Y. Song, "Financial distress prediction using a corrected feature selection measure and gradient boosted decision tree," *Expert Systems with Applications*, vol. 190, p. 116202, Mar. 2022, doi: 10.1016/j.eswa.2021.116202.
[42] M. Noorunnahar, A. H. Chowdhury, and F. A. Mila, "A tree based eXtreme gradient boosting (XGBoost) machine learning model to forecast the annual rice production in Bangladesh," *PLOS ONE*, vol. 18, no. 3, pp. 1–15, Mar. 2023, doi: 10.1371/journal.pone.0283452.
[43] M. Bregere and R. J. Bessa, "Simulating tariff impact in electrical energy consumption profiles with conditional variational autoencoders," *IEEE Access*, vol. 8, pp. 131949–131966, 2020, doi: 10.1109/access.2020.3009060.
[44] G. Jung and S.-Y. Choi, "Forecasting foreign exchange volatility using deep learning autoencoder-LSTM techniques," *Complexity*, vol. 2021, pp. 1–16, Mar. 2021, doi: 10.1155/2021/6647534.
[45] G. Alicioglu and B. Sun, "A survey of visual analytics for explainable artificial intelligence methods," *Computers and Graphics*, vol. 102, pp. 502–520, Feb. 2022, doi: 10.1016/j.cag.2021.09.002.
[46] E. Ayan and S. Eken, "Detection of price bubbles in Istanbul housing market using LSTM autoencoders: a district-based approach," *Soft Computing*, vol. 25, no. 12, pp. 7957–7973, Mar. 2021, doi: 10.1007/s00500-021-05677-6.

[47] J. Luo, C. Zhao, Q. Chen, and G. Li, “Using deep belief network to construct the agricultural information system based on internet of things,” *The Journal of Supercomputing*, vol. 78, no. 1, pp. 379–405, May 2021, doi: 10.1007/s11227-021-03898-y.
[48] D. Santoro and L. Grilli, “Generative adversarial network to evaluate quantity of information in financial markets,” *Neural Computing and Applications*, vol. 34, no. 20, pp. 17473–17490, May 2022, doi: 10.1007/s00521-022-07401-3.
[49] Y. Wang *et al.*, “Cycle-SNSPGAN: towards real-world image dehazing via cycle spectral normalized soft likelihood estimation patch GAN,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 11, pp. 20368–20382, Nov. 2022, doi: 10.1109/tits.2022.3170328.
[50] H. Ni, L. Szpruch, M. Sabate-Vidales, B. Xiao, M. Wiese, and S. Liao, “Sig-wasserstein GANs for time series generation,” *Proceedings of the Second ACM International Conference on AI in Finance*, Nov. 2021, doi: 10.1145/3490354.3494393.
[51] H. H. Kim, “A dynamic analysis of household debt using a self-organizing map,” *Empirical Economics*, vol. 62, no. 6, pp. 2893–2919, Aug. 2021, doi: 10.1007/s00181-021-02120-5.
[52] E. K. Ampomah, G. Nyame, Z. Qin, P. C. Addo, E. O. Gyamfi, and M. Gyan, “Stock market prediction with Gaussian Naïve Bayes machine learning algorithm,” *Informatica*, vol. 45, no. 2, pp. 243–256, Jun. 2021, doi: 10.31449/inf.v45i2.3407.
[53] M. Norouzi, J. Aghaei, T. Niknam, M. Alipour, S. Pirouzi, and M. Lehtonen, “Risk-averse and flexi-intelligent scheduling of microgrids based on hybrid Boltzmann machines and cascade neural network forecasting,” *Applied Energy*, vol. 348, p. 121573, Oct. 2023, doi: 10.1016/j.apenergy.2023.121573.
[54] E. Oostwal, M. Straat, and M. Biehl, “Hidden unit specialization in layered neural networks: ReLU vs. sigmoidal activation,” *Physica A: Statistical Mechanics and its Applications*, vol. 564, p. 125517, Feb. 2021, doi: 10.1016/j.physa.2020.125517.
[55] D. Mai and K. Pukthuanthong, “Economic narratives and market outcomes: a semi-supervised topic modeling approach,” *SSRN Electronic Journal*, vol. 24, pp. 1–87, Dec. 2021, doi: 10.2139/ssrn.3990324.
[56] C. Xu *et al.*, “HGNN: hierarchical graph neural network for predicting the classification of price-limit-hitting stocks,” *Information Sciences*, vol. 607, pp. 783–798, Aug. 2022, doi: 10.1016/j.ins.2022.06.010.
[57] F. Jin, R. Li, and H. Wu, “Graph neural network-based similarity relationship construction model for geospatial services,” *Geo-spatial Information Science*, vol. 26, pp. 1–15, Nov. 2023, doi: 10.1080/10095020.2023.2273820.
[58] S. Barak, E. Mirafzali, and M. Joshaghani, “Improving deep learning forecast using variational autoencoders,” *SSRN Electronic Journal*, vol. 21, pp. 1–32, Jan. 2022, doi: 10.2139/ssrn.4009937.
[59] M. Mele, C. Magazzino, N. Schneider, and F. Nicolai, “Revisiting the dynamic interactions between economic growth and environmental pollution in Italy: evidence from a gradient descent algorithm,” *Environmental Science and Pollution Research*, vol. 28, no. 37, pp. 52188–52201, May 2021, doi: 10.1007/s11356-021-14264-z.
[60] S. K. Sahu, A. Mokhade, and N. D. Bokde, “An overview of machine learning, deep learning, and reinforcement learning-based techniques in quantitative finance: recent progress and challenges,” *Applied Sciences*, vol. 13, no. 3, pp. 1–27, Feb. 2023, doi: 10.3390/app13031956.
[61] S. Ma, H. Liu, N. Wang, L. Huang, and H. H. Goh, “Incentive-based demand response under incomplete information based on the deep deterministic policy gradient,” *Applied Energy*, vol. 351, p. 121838, Dec. 2023, doi: 10.1016/j.apenergy.2023.121838.
[62] S. Otabek and J. Choi, “Multi-level deep Q-networks for Bitcoin trading strategies,” *Scientific Reports*, vol. 14, no. 1, pp. 1–20, Jan. 2024, doi: 10.1038/s41598-024-51408-w.
[63] B. Hambly, R. Xu, and H. Yang, “Recent advances in reinforcement learning in finance,” *Mathematical Finance*, vol. 33, no. 3, pp. 437–503, Apr. 2023, doi: 10.1111/mafi.12382.
[64] B. Baldacci, I. Manziuk, T. Mastrolia, and M. Rosenbaum, “Market making and incentives design in the presence of a dark pool: A stackelberg actor–critic approach,” *Operations Research*, vol. 71, no. 2, pp. 727–749, Mar. 2023, doi: 10.1287/opre.2022.2406.
[65] N. Baard and T. L. Van Zyl, “Twin-delayed deep deterministic policy gradient algorithm for portfolio selection,” *IEEE Symposium on Computational Intelligence for Financial Engineering and Economics (CIFEr)*, vol. 2022, pp. 1–8, May 2022, doi: 10.1109/cifer52523.2022.9776067.
[66] F.-F. He, C.-T. Chen, and S.-H. Huang, “A multi-agent virtual market model for generalization in reinforcement learning based trading strategies,” *Applied Soft Computing*, vol. 134, p. 109985, Feb. 2023, doi: 10.1016/j.asoc.2023.109985.
[67] L. Bisi, D. Santambrogio, F. Sandrelli, A. Tirinzoni, B. D. Ziebart, and M. Restelli, “Risk-averse policy optimization via risk-neutral policy optimization,” *Artificial Intelligence*, vol. 311, p. 103765, Oct. 2022, doi: 10.1016/j.artint.2022.103765.
[68] Y. Zhao and Z. Chen, “Forecasting stock price movement: new evidence from a novel hybrid deep learning model,” *Journal of Asian Business and Economic Studies*, vol. 29, no. 2, pp. 91–104, Aug. 2021, doi: 10.1108/jabes-05-2021-0061.
[69] M. Durairaj and B. H. K. Mohan, “A convolutional neural network based approach to financial time series prediction,” *Neural Computing and Applications*, vol. 34, no. 16, pp. 13319–13337, Mar. 2022, doi: 10.1007/s00521-022-07143-2.
[70] J. Guo, P. Lin, L. Zhang, Y. Pan, and Z. Xiao, “Dynamic adaptive encoder-decoder deep learning networks for multivariate time series forecasting of building energy consumption,” *Applied Energy*, vol. 350, p. 121803, Nov. 2023, doi: 10.1016/j.apenergy.2023.121803.
[71] J. Y.-L. Chan, K. T. Bea, S. M. H. Leow, S. W. Phoong, and W. K. Cheng, “State of the art: a review of sentiment analysis based on sequential transfer learning,” *Artificial Intelligence Review*, vol. 56, no. 1, pp. 749–780, Apr. 2022, doi: 10.1007/s10462-022-10183-8.
[72] Y. Zheng, Z. Xu, and A. Xiao, “Deep learning in economics: a systematic and critical review,” *Artificial Intelligence Review*, vol. 56, no. 9, pp. 9497–9539, Jul. 2023, doi: 10.1007/s10462-022-10272-8.
[73] C.-X. Wan and B. Li, “Financial causal sentence recognition based on BERT-CNN text classification,” *The Journal of Supercomputing*, vol. 78, no. 5, pp. 6503–6527, Oct. 2021, doi: 10.1007/s11227-021-04097-5.
[74] M. Suzuki, H. Sakaji, M. Hirano, and K. Izumi, “Constructing and analyzing domain-specific language model for financial text mining,” *Information Processing and Management*, vol. 60, no. 2, p. 103194, Mar. 2023, doi: 10.1016/j.ipm.2022.103194.
[75] J. Wu, K. Xu, X. Chen, S. Li, and J. Zhao, “Price graphs: utilizing the structural information of financial time series for stock prediction,” *Information Sciences*, vol. 588, pp. 405–424, Apr. 2022, doi: 10.1016/j.ins.2021.12.089.
[76] T. Mashadihasanli, “Stock market price forecasting using the ARIMA model: an application to Istanbul, Turkiye,” *Journal of Economic Policy Researches/İktisat Politikası Araştırmaları Dergisi*, vol. 9, no. 2, pp. 439–454, Jul. 2022, doi: 10.26650/jepr1056771.
[77] J. Bauer and D. Jannach, “Improved customer lifetime value prediction with sequence-to-sequence learning and feature-based models,” *ACM Transactions on Knowledge Discovery from Data*, vol. 15, no. 5, pp. 1–37, May 2021, doi: 10.1145/3441444.
[78] F. Bozyiğit and D. Kılınç, “Practices of natural language processing in the finance sector,” *Accounting, Finance, Sustainability, Governance and Fraud: Theory and Application*, vol. 2, pp. 157–170, May 2022, doi: 10.1007/978-981-16-8997-0_9.
[79] J. A. Garcia-Diaz, F. Garcia-Sanchez, and R. Valencia-Garcia, “Smart analysis of economics sentiment in Spanish based on linguistic features and transformers,” *IEEE Access*, vol. 11, pp. 14211–14224, 2023, doi: 10.1109/access.2023.3244065.

[80] M. S. I. Malik, U. Cheema, and D. I. Ignatov, "Contextual embeddings based on fine-tuned urdu-BERT for urdu threatening content and target identification," *Journal of King Saud University - Computer and Information Sciences*, vol. 35, no. 7, p. 101606, Jul. 2023, doi: 10.1016/j.jksuci.2023.101606.
[81] D. Rao, S. Huang, Z. Jiang, G. G. Deverajan, and R. Patan, "A dual deep neural network with phrase structure and attention mechanism for sentiment analysis," *Neural Computing and Applications*, vol. 33, no. 17, pp. 11297–11308, Jan. 2021, doi: 10.1007/s00521-020-05652-6.
[82] F. A. Dael, Ö. Ç. Yavuz, and U. Yavuz, "Stock market prediction using generative adversarial networks (GANs): Hybrid intelligent model," *Computer Systems Science and Engineering*, vol. 47, no. 1, pp. 19–35, 2023, doi: 10.32604/csse.2023.037903.
[83] E. Arslan and A. Güneş, "Fraud detection in enterprise resource planning systems using one-class support vector machine combined with convolutional neural network: the case of spor Istanbul," *Annals of Applied Sport Science*, vol. 11, no. 2, pp. 1–16, Aug. 2023, doi: 10.61186/aassjournal.1222.
[84] Y. Chabchoub, M. U. Togbe, A. Boly, and R. Chiky, "An in-depth study and improvement of isolation forest," *IEEE Access*, vol. 10, pp. 10219–10237, 2022, doi: 10.1109/access.2022.3144425.
[85] I. E. Livieris, S. Stavroyiannis, E. Pintelas, T. Kotsilieris, and P. Pintelas, "A dropout weight-constrained recurrent neural network model for forecasting the price of major cryptocurrencies and CCi30 index," *Evolving Systems*, vol. 13, no. 1, pp. 85–100, Jan. 2021, doi: 10.1007/s12530-020-09361-2.
[86] Z. Fang, X. Ma, H. Pan, G. Yang, and G. R. Arce, "Movement forecasting of financial time series based on adaptive LSTM-BN network," *Expert Systems with Applications*, vol. 213, p. 119207, Mar. 2023, doi: 10.1016/j.eswa.2022.119207.
[87] F. Bova, A. Goldfarb, and R. G. Melko, "Quantum economic advantage," *Management Science*, vol. 69, no. 2, pp. 1116–1126, Feb. 2023, doi: 10.1287/mnsc.2022.4578.
[88] S. Wilkens and J. Moorhouse, "Quantum computing for financial risk measurement," *Quantum Information Processing*, vol. 22, no. 1, pp. 1–38, Jan. 2023, doi: 10.1007/s11128-022-03777-2.

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