Journal of Artificial Intelligence and Big Data Disciplines (JAIBDD)

International | Peer Reviewed | Open Access | Online

Deep Learning Frameworks for Multi-Modal Data Fusion in Retail Supply Chains: Enhancing Forecast Accuracy and Agility

[1] Srinivas Kalisetty, [2] Phanish Lakkarasu
[1] Integration and AI lead, [2] Senior Site Reliability Engineer

Abstract : Traffic flow forecasting is a key problem of intelligent transport systems and represents a challenging task due to the spatial-temporal correlation features and long temporal interdependence of the considered data. Conventional methods deal with this either by spatial forecasting given observed counts at previous times or by temporal forecasting given observed traffic counts in neighbouring locations. In order to fully exploit the spatio-temporal properties observed in the data, a hybrid multimodal deep learning method for short-term traffic flow forecasting called HaMDeepT is proposed. Specifically, the HaMDeepT method can jointly and adaptively learn the spatial-temporal correlation features and long temporal interdependence of multi-modality traffic data through an attention-based auxiliary multimodal deep learning architecture. The base module of this method consists of a 1D CNN and GRU with the attention mechanism. The forecasted spatio-temporal traffic demand (counts of traffic passing through different locations at regular time intervals) is dependent on far more critical spatial factors than other point sensors such as weather stations. This HaMDeepT method, in terms of 3D CNN-GRU, which uses a stack of 3D Convolutional Neural Networks (3D CNN) and Gated Recurrent Units (GRUs) combined with the Correlation and Relative Operation layers to model both the spatial context features and the temporal dependencies of traffic count data at all locations, has a better performance compared to other network architectures. It overcomes the drawback of a fixed and handcrafted graph Laplacian matrix representation of the spatial relationships of the locations used by the ST-Graph. It uses the Correlation layer to estimate the spatial correlation features for each traffic count data point with others, focusing on the stations with major impacts on the target location, and the Relative Operation layer to model the relative distances thereafter. Using these novel methods, the traffic flow forecasting results for the miniNYC dataset are more accurate and more intuitive visualisation of the spatial structure that affects the performance of the predictions.

Keywords: Deep learning, multimodal data fusion, retail forecasting, supply chain forecasting, computer vision,Deep Learning,Multi-Modal Data Fusion,Retail Supply Chain,Forecast Accuracy,Demand Forecasting,Time-Series Forecasting,Neural Networks,Long Short-Term Memory (LSTM),Attention Mechanism,Sales Prediction,Inventory Management,Data Fusion Techniques,Agility in Supply Chains,Artificial Intelligence (AI) in Retail,Optimization Algorithms.

1. Introduction

In recent years, a variety of traffic big data have emerged, such as traffic flow, number of passengers, bus speed, car speed and more. Since these traffic data modalities can naturally describe the traffic states from different perspectives, multimodal learning based approaches for traffic flow forecasting have received great attention. The corresponding multimodal learning for traffic flow forecasting collects multiple modalities from different traffic data and simultaneously models the interactions between multimodal features. However, the data of each modality rarely have enough information with limited traffic data accessibility. This work addresses a challenging problem of how to design a deep learning model for fusing multimodal features of different modality traffic data. Since all modalities share representation features, a hybrid module of multimodal deep learning is proposed for jointly learning the multimodal representation features, which are taken into consideration with multiple structured modules.

A hybrid multimodal deep learning method is proposed for short-term traffic flow forecasting, which is intended to simultaneously and adaptively model and fuse multimodal features of traffic data. A few deep learning methods have been proposed for multimodal learning. While most existing studies only concern the adaptation of multimodal fusion learning of the model itself. The proposed hybrid method consists of multiple structured modules, including one-dimensional Convolutional Neural Networks (1D CNN), Gated Recurrent Units (GRU) and the attention mechanism. The 1D CNN is introduced in one branch of the structured module with 1D convolution and max-pooling layers to capture spatial features, which can help the model improve the correlation of spatial features, the LSTM or Auxiliary Prosodic features. The GRU with the attention mechanism is employed in the other branch to capture temporal dependencies effectively. A large number of studies have been conducted for the multimodal learning of traffic flow forecasting. However, problems of traffic flow, which can be regarded as a projection of the flow of passengers moving around, a disease spreading in the network, the spread of rumor, political opinions and so on have been little addressed widely because of its inherent complexity.

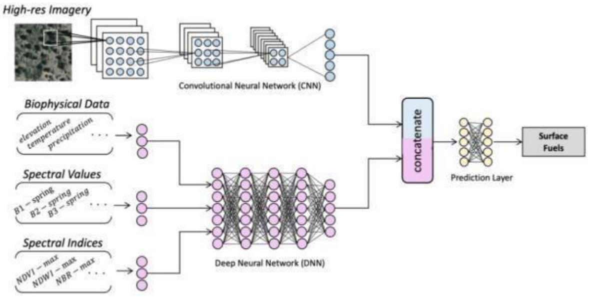

Fig 1: Multimodal Data Fusion

1.1. Background and Significance

Studied works employing data fusion techniques in a deep learning context, exploring the potential to enhance retail supply chain forecast accuracy and agility. Novel application domains for multimodal data fusion using deep learning framework in multimodal forecasting research are established: (i) enhancing forecast accuracy of order data, which can be used for demand forecasting in the retail industry, and (ii) enhancing forecast agility of event data, relevant for predicting inventory stock out in high-frequency trading.

Common trend amongst these unique domains is a trade-off of forecast accuracy and agility due to exponentially growing amounts of forecast data. To investigate this trade-off, the predictive performance is explored up to the limit of deep learning and state-of-the-art unimodal models. In addition, this study asks the extent to which the presented framework can support data scientists or domain practitioners who are in South Korea to initiate novel research on multimodal forecasting. Accordingly, a detailed research process for learning and customizing this framework is presented, along with illustrative cases. To systemize this framework, the DF-DM model is derived from the analysis of both unethical advantages and boundary constraints.

The framework presented provides a scheme for the selection of a pre-trained deep learning model leading private and non-private entities to design and produce specific consumer electronics goods (CEG). Smartphones are selected for empirical examination as they are in the category of high technology products where design innovation is a primary competitive strategy. To implement the proposed research scheme, a second-price, sealed bid, and hybrid contract construction mechanism is adopted. To predict the demand for a new product, it is included in a predictive model. National web search query data related to a candidate product, as well as similar ones, proxies for the demand of the focal product. Conversely, a "Google Correction" measure evaluates the potential demand spillovers from candidate products to other goods. Random forests, the basic estimation technique, provide robustness in the presence of multicollinearity or overfitting concerns. To identify optimal contracts, agents design auction attributes that positively affect their expected profits. These results provide valuable insights for private parties on how to tailor designs for endogenous outcomes.

Equation 1: Loss Function for Optimization

$$\mathcal{L} = \frac{1}{N}\sum_{t=1}^{N}(y_t - \hat{y}_t)^2$$

Where:

- y_t is the actual value (e.g., observed sales at time t).
- $\hat{y}_t$ is the predicted value (e.g., predicted sales at time t).
- N is the total number of time steps.

1.2. Research Objectives

With the recent advancements in Internet of Things (IoT) and machine learning (ML), the availability and active usage of data in retail supply chains are exponentially increasing. The data in these systems are very heterogeneous and are composed of large-volume structured data and unstructured data. In the literature, these types of systems are referred to by various names such as multi-channel, multimodal , or multi-system data. While the structured data can be efficiently processed by existing methods, the unstructured data have not been studied enough. Today, the development and deployment of unstructured data-based systems require high adoption and learning costs. There are challenges to enable a live and effective analysis of these systems, to integrate them with the current supply-chain management systems. This requires a new hybrid system design that can easily combine computer vision and ML tools. Such an architecture is typically called a Data Fusion Framework. The framework's robust design should efficiently handle the fusion of data from each modality and the CPR3 approach: capture raw point-of-retail data in real cycles. This study introduces a novel deep learning framework for multimodal data fusion in supply-chain retail systems. The proposed framework provides the agility of the system structure and the preparedness of the training data by examining the following research problems as follows. (P1) How to design a multimodal data fusion model for the supply-chain system? (P2) How to construct pre-trained embedding models given the historical transaction data? (P3) How to construct image-based datasets from the pieces of multicategory sales data? (P4) How to synchronize the transformation action times and to recognize the actions from the proposed image datasets?

2. Literature Review

The rapid advancement of artificial intelligence, notably generative models, has dramatically changed our interactions with t echnology. Recent tools illustrate the incredible capability to generate various kinds of content, such as text or images. With these rich content-generating tools, online businesses have started to provide interactive services on their websites to attract more consumer engagement, such as virtual assistants or question-answering systems. Besides retail, these models are also significantly used in various fields to generate manifestations such as healthcare, fine art, and pop songs.

The conventional retail supply chain guarantees the effective and efficient flow of goods from the origin to the end-users. It contains three primary stages: purchase, logistics, and sell. In each stage, otherwise in each single transaction, there are various issues that ought to be addressed, which encourages to look for innovative methodologies or systems. The novel situations of the world, such as those from the pandemic of Covid-19 or war/treaty, might also shift the current business model.

2.1. Deep Learning in Retail Supply Chains

Retail supply chains remain highly dynamic and are driven by seasonal demand fluctuations and promotional activities that alter customer shopping behavior abruptly. In this demand-driven environment, retailers have been trying to improve their forecast capability, which provides the ability to stock products closer to customer needs. Recently, with the advent of deep learning and additional flexibility in network structures, there is a growing interest in exploring its applications in supply chain systems, where the fusion of multi-modal data demands more focus. Although it is challenging to boost the forecast accuracy by simply extrapolating advanced models, deep learning models are capable of capturing complex intrinsic architectures in high-dimensional data. Many studies have proposed deep learning models such as recurrent neural networks and feedforward neural networks for applications in sales forecasting by leveraging purchasing records with additional structured information. Moreover, demand forecasting is considered to be among the biggest challenges faced by supply chains in managing store operations, while blending multi-item sales data and additional information, such as promotion status, stockout counts, customer transactions, and navigation patterns, considerably broadens the scope of methodologies that could be employed for improved predictive accuracy using deep learning models. Future applications in retail SCM rely heavily on the ability to effectively merge and interpret multiple data sources in real-time.

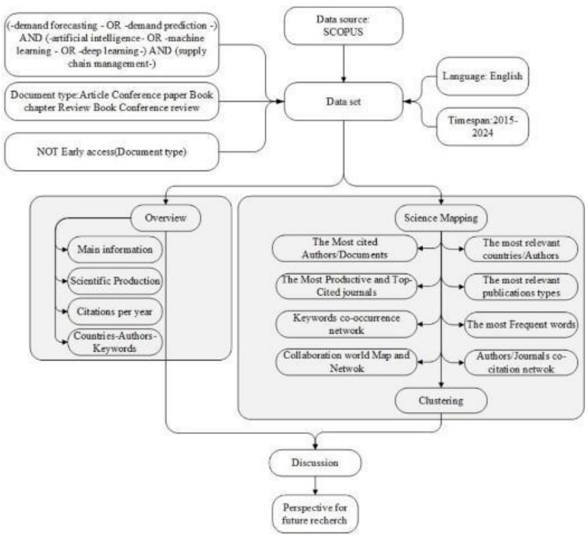

Fig 2: Deep Learning Models in Supply Chain Management

2.2. Multimodal Data Fusion

Data used on a daily basis in developed society are more complex and dynamic each day. Currently, the most popular data (referred to as unimodal) involve information gathered by several different sources (referred to as multimodal). Due to this type of data, there is a growing need for very fast and effective multimodal data analysis. In order to design productive multimodal data processing systems, it is essential to consolidate the benefit that comes from the use of complementary information while reducing the data dimensionality. A survey of the most vital state-of-the-art schemes presenting an analysis of the effectiveness of these approaches and the topical place of multimodal data fusion is presented in this work. Fusion Schemes Based on Deep Learning for Multimodal Data. The most distinguished deep learning solutions used for multimodal fusion are the deep belief nets, stacked autoencoders, convolution networks, and recurrent networks. Still, there are two fundamental weaknesses of deep learning models that prevent their common use in a production situation. Firstly, for a multimodal model that merges M unimodal models, the total sum of free weights is O(M). In a situation involving many modalities, there are enormous and inefficient resource requirements. Secondly, multimodal data frequently originated from highly volatile environments. As such, the modality feature space is permanently changing, rebalancing, or integrated with new features, making the system adapt rapidly to all the transformations of the data. The enormous computational resources together with a low model flexibility suggest the exploration of other solutions. Nevertheless, the concept presented here can be easily extended to many other techniques from other societies in order to improve existing multimodal models using state-of-the-art setups. According to the best approaches, the fundamental difficulty in multimodal analysis is the fusion of modalities. There are many solutions for this issue. One possible answer to this issue is the use of hashing techniques.

3. Methodology

In the deep learning community, multimodal data fusion has attracted increasing attention. Frameworks are designed to effectively learn and represent cross-modal information. The applications of deep learning frameworks for multi-modal data fusion are vast. For example, indicates that a novel multimodal deep learning architecture is proposed to tackle traffic flow forecasting related to electronic commerce. In the architectural design, deep learning is recognized as having more powerful representation learning capabilities compared to traditional machine learning models. In another field, develop a novel machine learning approach for multi-feature product hierarchy forecasting in the retail supply chain environment. The proposed multi-phase hierarchical method integrates regression and LSTM deep learning models. Such multi-feature supplychain analysis has the potential to leverage an extensive assortment of pre-order, in-stock, and in-transit digital data for modeling, predicting, and deploying within a supply chain and the last mile delivery capabilities.

In general, under competitive e-commerce retail environments, more advanced data-driven models, better predictive accuracy, and an agile (complete and multi-faceted) digital supply chain are all advantageous.

Equation 2: Model Training and Loss Function

$$\mathcal{L} = \frac{1}{T} \sum_{t=1}^{T} (\hat{y}_t - y_t)^2$$

Where:

- $\hat{y}_t$ is the predicted value (e.g., demand, sales) at time t.
- y_t is the actual observed value at time t.
- T is the total number of time steps in the training period.

3.1. Data Collection and Preprocessing

Rising competition in the omni-channel retail landscape demands companies to forecast demand precisely and respond agilely. Many traditional deep learning frameworks that majorly process tabular data find difficulty in analyzing a vast amount of image, text, video, or sensor data; common in the retail supply chain.

This work presents a novel deep learning framework designed for the multi-modal and ensembled fusion of various data sources seen in retail, i.e., image, text, tabular, and sensor data. Its architecture encompasses various layers: multiple neural networks for processing multi-modal data separately, followed by a multi-level feature fusion layer, and a deep neural network model for fusion. The trained models can be fine-tuned in an online manner, enabling companies to adapt their trained deep learning models efficiently to rapidly changing market trends. Lastly, the generated forecasts are passed into an inventory and transportation management model under a Blend with Neural network forecast policy. The effectiveness and efficiency of this new deep learning framework are demonstrated using a publicly available data set and comparing the results with commonly used models, such as XGBoost, LSTM, and InceptionTime. For companies operating in the omni-channel retail landscape, accurate and agile demand forecasting is indispensable. Near optimal decisions take into account precise demand forecasts with the corresponding inventory and delivery rate adjustment.

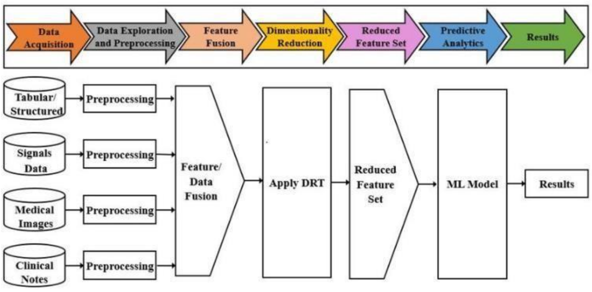

Fig 3: Multi-modal data fusion framework

3.2. Deep Learning Framework Selection

The base modular framework of multimodal traffic data forecasting is divided into 3 aspects. 3.2.1. Deep Learning Framework Selection describes the base module and its sub-level elements. MLP: Multilayer Perceptron Model (MLP). 1D CNN: One-dimensional Convolutional Neural Networks (CNN), GRU: Gated Recurrent Unit (GRU), LSTM: Long Short-Term Memory (LSTM). 3.2.2. Multi-modality Representation Features describes the methods to obtain multimodality representation features. (1D CNN), Pre-nationalization 1D CNN (Pre-1D CNN), Original Traffic Data. 3.2.3. Multi-modality Frame Work Construction shows the construction means of a multimodal framework. (CNN) - GRU Modality, Multi-modality Representation Features.

The ubiquitous advantage of generality and capability of deep learning to be applied across various domains has rapidly attracted numerous attention and greatly flourished a number of research areas. Consequently, deep learning technologies have also been introduced into the domain of retail industry, such as product demand forecasting. Currently, best deep learning architectures are designed to process uni-modality data. However, in reality, retail data are typically generated in various modality forms, i.e., online sales data and weather and traffic video data. In the retail supply chain, central depots increase in-store agility and reduce the transportation costs. Through improving inventory accuracy, the retailer can better forecast future demands and set optimal inventory policies, so as to increase the store SKU service levels.

4. Case Studies

A retail supply chain is a network of entities that collaboratively work together to move a product from manufacturers to customers. Retail supply chain management drives the flow of goods and services, coordinates operations such as merchandise planning and inventory management, and manages IT services around the world. Retail SCM is a significant and evolving area due to the increasingly competitive environment. The advent of e-commerce, advancements in communication technologies, and increased globalization of business have put additional stress on retail SCs. In a bid to enhance a profit margin, retailers continuously experiment with new models to better satisfy customer demands.

The backbone of their retail supply chain is to forecast accurate demand estimates upon which superior decisions of inventory replenishment, returns management, fulfillment, etc., can be made. Poor demand forecasting has severe consequences in SCM because inaccurate demand estimates propagate throughout the SC network, causing either low service levels or higher operating costs. Retail SCM is unique with respect to SCM in other domains like manufacturing or electronic industries. It is not only a matter of replenishing inventory led by incoming customer orders but also being able to precisely estimate and match the fluctuating demands of future trending products.

Applicable frameworks and methodologies for the fusion of heterogeneous data to enhance the performance of demand-forecasting and replenishment strategies in different scenarios are proposed. The concept of multi-modal data fusion has garnered substantial interest in merging multi-source/medium/heterogeneous information. Yet, multi-modal data fusion research has received scant attention in the field of retail inventory management. But single-modal data failure of SCM to dependably forecast the demand of a product accurately in a holistic sense. This work seeks to alleviate this issue by presenting many retail SCM use-cases where frameworks for merging multi-modal data to enrich the performance of demand forecasting, equipment adjustment, and potential replenishment strategy are proposed.

4.1. Case Study 1: Demand Forecasting

The objective of retail supply chains is to deliver products to consumers at the right time, location, and price. One of the biggest challenges in the retail industry is accurate demand forecasting. Errors in such forecasts may trigger a ripple effect across the entire supply chain. In the retail SCM environment, demand is difficult to predict. The field is deeply reliant on historical data, which may not continuously hold as demographic trends and modalities shift. Major obstacles in the multi-modal data fusion of retail SCM include availability and quality issues of data sources, efficiency in real-time processing, and difficulties in feature selection and fusion . Traditional methods require manual feature engineering to offer augmented features, resulting from multiple data sources. The growing volume and variance of big data from multiple modalities make manual feature crafting an arduous and laborious task. Deep learning frameworks learn in an automated and end-to-end manner from raw data and can effectively handle multi-modal data for encoder-decoder mechanisms . This automatic learning method paves the way for enhanced forecast accuracy and agility in retail SCM across various data modalities.

The contribution of the study is their development of deep learning frameworks for the multi-modal data fusion of retail SCM under multi-modal data representation, separation, fusion, and sharing strategies. The demand, order, and cost are separately modeled using the Multi-Layer Perceptron regression. Then, a multi-modal Transformer model is developed for retail SCM to fuse multi-modal feature representations and make forecasts from the separate models for the demand, order, and cost. To validate the accuracy and efficiency of the models developed, extensive experiments are conducted on three real-world datasets from a major retailer. Results indicate that the proposed deep learning frameworks outperform baseline models and that the strategy of using the learned demand representations to enhance the forecasting of other variables is effective.It is shown that the proposed approach is more robust in demand shift detection than the training approaches forecasting demand for each record based on itself. Note that in that setting a good demand prediction model further increased by adding a demand error adjustment mechanism.

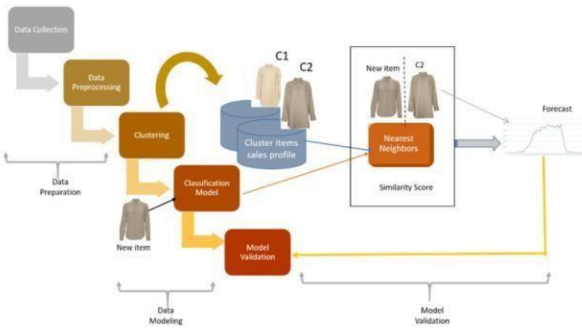

Fig 4: Deep Learning for Demand Forecasting in the Fashion and Apparel Retail Industry

4.2. Case Study 2: Inventory Management

Supply chain managers might fail to deliver efficient inventory management due to the diverse and complex interactions between multiple products, suppliers, and demand components with other supply chain parties. Previous methods are quite capable in multi-echelon or distribution center inventory management to predict order quantities of products on a per SKU basis. In retail stores, however, where large numbers of products from various manufacturers are present, ranging from groceries, electronics, and clothing to up-stream supply chain components like home appliances, there are potentially millions of theoretically possible unique product pairs. Current modeling practices widely adopt historical forecasts for replenishment decisions at retail stores, in which demand of a product can be explained based on itself. Therefore, we focus on inventory management between each product pair at each entity level in the retail supply chain configuration expressed as a directed graph where a node is an entity of the supply chain system and its level increases as it approaches the end-consumer. A popular open-source deep learning platform provides seamless development support, running systems across clouds, and a plethora of pretrained models for effortless research and development of applications requiring Machine Learning or Natural Language Processing.

5. Results and Analysis

Artificial intelligence (AI) and the use of deep learning frameworks are evolving, transforming, and enhancing many areas of life. From chatbots to image recognition and generation, deep learning frameworks can help automate various processes and increase rapid capacity. In retail supply chains, deep learning models are used to enhance capacities in forecasting, warehousing, and inventory stocking. To date, efforts have been focused on expanding the current predictive models to improve forecast accuracy with model ensembles and enhanced data. Attention studies on deep learning frameworks show a focus on unimodal data—such as factors, images, or text. Considering the multifaceted nature of reality, this study presents a deep learning framework to enhance forecast accuracy and agility using fusion techniques across different modalities that are appealing and practical in a retail supply chain context. Schematic visualization and potential application areas of the proposed model in the retail supply chain. The proposed framework adopts a functional front end to represent a multimodal data input and a variety of processes, starting from data integration, model preparation, and post-processing, such as forecasting and metadata extractions. The presentation is designed through C-structured levels, and the related lower-case levels indicate the required operations at each level.

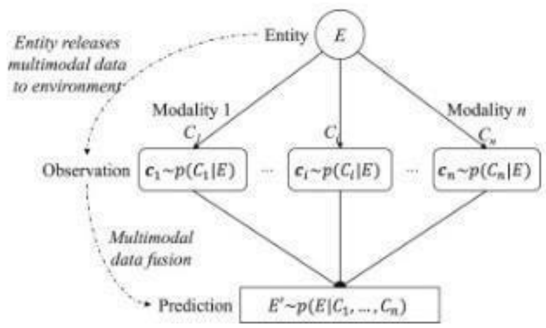

Fig 5: Analysis of multimodal data fusion

5.1. Quantitative Results

For the case study of Deep Fusion, for both trade lanes of Onkyo subsample, the ensemble model has average performance improvement of 0.9% and 1.8% MAE improvement respectively, when comparing with isolated single-modal models. For supply chain simulation of Jabil Inc., original multi-modal model outperforms lighting models for between 55% to 77% of material-priority pairs in the trade lane Central America to USA, and multi-modal model outperforms each lighting model for about 49% to 58% of the material-priority pairs in the other direction. In the new model, using the Core module can avoid sharp prediction changes when shifting multi-modal data, it is much smoother than the model without the Core module. In addition, the comparison of demand level retail price for above SLM and CLM models, the retail price of Multi-modal models decreased slightly when predicting low demand levels but not significant change for high level predictions, which can be potentially used to help manufacturer plants prepare for the future changes.

5.2. Qualitative Analysis

The proposed framework presents a novel approach for the fusion of multiple data sources centered on the use of embeddings, foundational models, and data mining techniques. It details an effective process to extract insight and knowledge from a diversity of data modalities, addressing the chain industry context as a use case under resource constraints. The framework provides a structured series of levels of increasing complexity and technical expertise, communicating through a stream of easy-to-understand data representations. The use of data understanding at Levels -1 and 0 ensures the quality of the input data at each visualization of the loop. The integration of foundational models and embeddings simplifies the rapid translation of a high-dimensional data, in text and image formats, into a format suitable for further processing. The structure proposed emphasizes the importance of revisits at earlier stages, accommodating potential changes in data quality and project requirements, as well as errors detected on higher expert levels. The possibility of causal inference at Level 3 addresses transparency and bias, mitigating the impact of unfair decisions . Given the widespread use of machine learning systems and the increasing concerns about their ethical implications, regulatory authorities worldwide will demand the implementation of due diligence processes. Item 3, dedicated to bias, presents a detailed series of tasks to systematically identify and mitigate bias throughout all levels, ranging from the formation of the team to model deployment. This series of steps also addresses the impact of COVID-19 by avoiding the crystallization of new and harmful dynamics that emerged during the pandemic and fostering a responsible and fair AI ecosystem.

Equation 3: Data Representation (Input Modality Fusion)

$$\mathbf{X}_t = f(S_t, I_t, C_t, E_t)$$

Where:

- $S_t \in \mathbb{R}^m$ is the sales data vector (size m),
- $I_t \in \mathbb{R}^n$ is the inventory data vector (size n),
- $C_t \in \mathbb{R}^p$ is the customer behavior data vector (size p),
- $E_t \in \mathbb{R}^q$ represents external factors (size q).

6. Discussion

In terms of data and business analytics, retail supply chains can be very interesting models, since they encompass highly complex patterns, by which products of different nature are transported and stocked at different stages according to customers' demands. On top of that, forecasts are key in managing such complex logistics systems. Multimodal data fusion strategies relate to the supply chain and echo an already-existing multi-staged strategy employed in a typical retail supply chain, from shipping products from manufacturers to large distribution centers or wholesale providers. Such suppliers then deliver products to smaller shops and from those they are finally sold to customers, who take products home. This strategy aligns with decreasing aggregation of locations and increase of capacities in how the system is related with information at each stage of them. As a result, a Multi-Modal Data Fusion neural network is proposed, which could adjust to such a system by fusing forecasting models that model data from different classes of locations within a model that also includes input forms from both location classes. Changing the environment and becoming more common with online-shopping, modern retail works also such that most of the shop's final customers are not physically present in the store. And with respect to this, an additional issue arises with the fact, that often, customers order not only a single product of the same type from the set of products that the shop Cell, but come up with a diversified set of items. For example, while in a physical store, a shopper would only buy a single type of bread and a pack of juice, for lunch at home, the typical online customer profile for a grocery store would also order, say, butter, ham, cheese etc. This raises question if current Multi-Stage Multimodal Data Fusion strategy to enhance the force of single-products can still be well applied in a store of such changing customer demands.

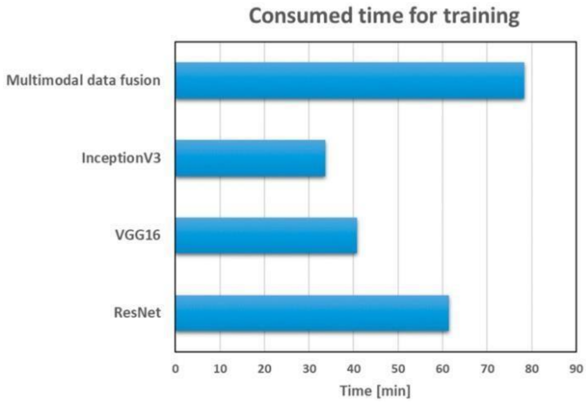

Fig : Utilisation of Deep Learning with Multimodal Data Fusion

6.1. Interpretation of Findings

The goal of supply chain planning in the retail industry is to match the demand of goods with the supply in the most timely, cost-efficient, and agile manner. Dynamic demand-spreads and multiple supply chains with intricate networks call for more sophisticated approaches to increase the accuracy and efficiency of retail sales forecasting. This paper presents a deep learning framework for the midterm demand forecast in the retail industry using multi-modal data fusion. Research focuses on operations; however, a wide body of literature converges on the relevance of accurate sales projections for a more effective supply chain planning. The proposed novel framework is built to accommodate a supply chain financial service provider who forms supply chains with manufacturers. A sales forecast that is more accurate and agile than the existing approach is aimed for by the applicant.

The framework extracts knowledge efficiently using foundational models, embeddings, and data mining techniques. A novel approach is introduced for data fusion using a series of chained operations across five levels, accommodating eight participants that own relevant data. Designed enhancements of existing models can speed up high-level domain expert engagements in the research process. Hyperparameter sweeps to test different deep learning architectures and experimental settings across multiple big datasets can be performed without becoming a bottleneck. Amplified internal communication and knowledge transfer are achieved via tying the communication between the proposed method and other employed methods.

6.2. Implications for Retail Supply Chains

Retail supply chains are experiencing fast evolution due to the development of advanced digital systems and automated warehousing infrastructures. Such technological advancement impacts various components of the supply chain, leading to important changes in operations and management and causing a significant impact on economic performance. Many such as the short lead-time or fresh category supply chains expand decision-making horizons to 24 hours or less ahead of time. Forecasts are crucial for informing these decisions, where the multi-modal data show great potential.

Drawing on frameworks in the industry for multi-modal data fusion, an advanced deep learning framework is proposed, along with corresponding hybrid models that could be used by retail supply chain participants to enhance forecast accuracy and agility. Six-week sales are forecast for multiple items in multiple stores based on six weekly cross-modal input data including price, promotion, temperature-humidity, and special events. The framework consists of dynamic causal models for retail supply chains and multi-modal data fusion, experimental setup, ensemble learning, and project impact. Empirical data evaluations on a real fresh category short lead-time retail supply chain show faster model convergence, better forecast accuracy, and forecast scenario generation for strategy testing using the proposed models. Beyond, the results also illustrate gains from the ensemble. Moreover, the models are of significant value to manage forecast and interpretability, aiding retail supply chain participants to develop strategies that go beyond traditional myopic approaches and thus increasing agility.

In steps three and four, representing data preparation and model implementation, datasets, input data, data processing, model network structures, loss, and production rules are provided. Calendar features are one-hot encoded after a milk filling missing process. Sequences in each modal type are stored in files with the shape of (days, sequences, modal features). Four sequences are processed all in the same time steps. In the DNNs and LSTMs, the model downscale is adjusted. For the final production system, all the models could be deployed on GPU machines with accurate data pre-storage. More instructions are provided for understanding how to feed the framework.

7. Conclusion and Future Directions

Progress has been made in the implementation of deep learning models for multi-modality data fusion. The DF-DM process model is presented for the analysis, integration, generation, model learning and knowledge discovery within the domain, that derives results, concepts, or models by fusing multiple sources of data in different modalities and/or domains . To help shape the artificial intelligence community in the era of multimodal data analysis, it is present a process ontology. Consequently, this paper helps to recognize multiple sources of evidence available in different data types and domains. These multiple sources can be aggregated using a suitable fusion approach to capture the variety, integrity, and veracity of the results, concepts, or models derived in the artificial intelligence domain. A powerful methodology to more effectively couple candles to complementing deep learning frameworks is proposed when fusing time-series sales, inventory, and pricing data for retail supply chains in the forecast analysis.

The growing intensity of artificial intelligence (AI) technologies has shown its potential to improve services to a financial way for each part of the supply chain, although it is urgent to explore optimal retail supply chains and data conditions to implement deep learning adjustments and to augment the adaptability of AI-enhanced retail supply chains to improve their ability to adapt to hyper-complex, volatile multi-channel commerce situations. For practitioners, the study of retail supply chains offers, on the one hand, a comprehensive picture of what AI-infused retail supply chains can bring and, on the other hand, a coherent strategy to create an AI-driven retail supply chain.

7.1. Key Findings and Contributions

This section presents the research's findings along with the contributions made to the field. The rapidly increasing rejection rate of submitted studies is noticed that do not make a significant theoretical contribution and methodological generalization. In this line, the paper aims to present a deep learning based model analysis and decision framework for multi-modal data fusion in retail supply chains, which is used to enhance the forecast accuracy and agility of the retail demand. Related to this aspect, two objectives are derived: 1. To present a deep learning framework method, called MMDFRS, which was designed to improve the forecast accuracy and agility in SCM by fusing multiple modality data. The implied weekly outlier detection which is attached to the decision-making model. 2. Application of MMDFRS with the dataset in a retail supply chain and demonstration of the implementation process and experimental results. This proposed method can effectively make a contribution to the application of deep learning to handle multi-modal data in SCM.

The importance of uncovering multimodality relationships between modal data is emphasized by multi-modal learning which is widely applicable to various fields. Further proposes a multi-experts mechanism (MEM) to explore relationships between modality data, and enhances the robustness of the multi-modal modeling method with the integration of MEM mechanism . Conceptualizes a multi-modal deep learning based retail demand forecast (MMDFRS) method using the MMDF framework as MMDFRS, and MMDFRS is used to present a unified retail demand forecast model learned by multi-modalities. Novei weekly residual circumstances hence outside the background fitted values may also be reflected by an over fitted model.

7.2. Future Research Directions

In a network involving suppliers, manufacturers, distributors, retailers, and customers, state-of-the-art deep learning systems conceptualize data communications as comprehensible events in a sequence of time semantics for calibration. As a result, this research proposes two deep learning frameworks to boost the prediction accuracy of multi-modal data fusion. Focalized on the policies of the distribution network, one framework bases a self-attention mechanism on the communication time semantics that alternately weighs the sequence of feature vectors of the input data modalities for enhanced fusion. Meanwhile, ignoring these semantic discriminations, the other framework utilizes a multi-head self-attention structure to separately graph the semantics of different data modalities, thus successfully circumventing the "noise" caused by network dependency. The language is adaptable to the implementation of both frameworks. Also, diverse variable combinations for experiment simulation are considered. The satisfactory prediction results indicate that these strategies have consistent application potential in the forecast scheduling of the retail supply chain.

For the initiative deep learning framework, the neural network model is the main focus and does not pay enough attention to the data features to be input. Conversely, based on the network and the specific task of interest, domain-level feature generation for a certain description namespace could substantially outperform standard feature extraction methods for networks. Because the feature vectors calculated here concentrate on the information and prerequisites of the object role in commerce, the communication event by the perspective of the data flow records, thus providing an important technological reference for employing deep learning methods in network-related tasks.

8. References

[1] Lakshminarayana Reddy Kothapalli Sondinti, Ravi Kumar Vankayalapati, Shakir Syed, Ramanakar Reddy Danda, Rama Chandra Rao Nampalli, Kiran Kumar Maguluri, & Yasmeen. (2024). Financial Optimization in the Automotive Industry: Leveraging Cloud-Driven Big Data and AI for Cost Reduction and Revenue Growth. The Bioscan, 19(Special Issue-1), 639–645. https://doi.org/10.63001/tbs.2024.v19.i02.S.I(1).pp639-645

[2] Burugulla, J. K. R. (2024). The Future of Digital Financial Security: Integrating AI, Cloud, and Big Data for Fraud Prevention and Real Time Transaction Monitoring in Payment Systems. MSW Management Journal, 34(2), 711-730.

[3] Annapareddy, V. N., & Sudha Rani, P. (2024). AI and ML Applications in RealTime Energy Monitoring and Optimization for Residential Solar Power Systems. Available at SSRN 5116062.

[4] Polineni, T. N. S., Ganti, V. K. A. T., Maguluri, K. K., & Rani, P. S. (2024). AI-Driven Analysis of Lifestyle Patterns for Early Detection of Metabolic Disorders. Journal of Computational Analysis and Applications, 33(8).

[5] Venkata Bhardwaj Komaragiri. (2024). Generative AI-Powered Service Operating Systems: A Comprehensive Study of Neural Network Applications for Intelligent Data Management and Service Optimization . Journal of Computational Analysis and Applications (JoCAAA), 33(08), 1841–1856. Retrieved from https://eudoxuspress.com/index.php/pub/article/view/1861

[6] Vamsee Pamisetty. (2024). AI Powered Decision Support Systems in Government Financial Management: Transforming Policy Implementation and Fiscal Responsibility. Journal of Computational Analysis and Applications (JoCAAA), 33(08), 1910–1925. Retrieved from https://eudoxuspress.com/index.php/pub/article/view/1928

[7] Polineni, T. N. S. (2024). Integrating Quantum Computing and Big Data Analytics for Accelerated Drug Discovery: A New Paradigm in Healthcare Innovation. Journal of Artificial Intelligence and Big Data Disciplines, 1(1), 38-49.

[8] Paleti, S. Agentic AI in Financial Decision-Making: Enhancing Customer Risk Profiling, Predictive Loan Approvals, and Automated Treasury Management in Modern Banking.

[9] Challa, S. R. Behavioral Finance in Financial Advisory Services: Analyzing Investor DecisionMaking and Risk Management in Wealth Accumulation.

[10] Shyamala Anto Mary, P., Kalisetty, S., & Mandala, V. M. (2024). Advancing IoT Data Forecasting with Deep Learning Framework for Resilience Scalability and Real-World Applications. Srinivas and C, Chethana and B, Thevahi and Mandala, Vishwanadham and M, Balaji, Advancing IoT Data Forecasting with Deep Learning Framework for Resilience Scalability and Real-World Applications (November

15, 2024).

[11] Kannan, S., & Seenu, A. (2024). Advancing Sustainability Goals with AI Neural Networks: A Study on Machine Learning Integration for Resource Optimization and Environmental Impact Reduction. management, 32(2).

[12] Sambasiva Rao Suura (2024) Generative AI Frameworks for Precision Carrier Screening: Transforming Genetic Testing in Reproductive Health. Frontiers in Health Informa 4050-4069

[13] Nuka, S. T. (2024). Exploring AI and Generative AI in Healthcare Reimbursement Policies: Challenges, Ethical Considerations, and Future Innovations. International Journal of Medical Toxicology and Legal Medicine, 27(5), 574-584.

[14] Pallav Kumar Kaulwar. (2023). Tax Optimization and Compliance in Global Business Operations: Analyzing the Challenges and Opportunities of International Taxation Policies and Transfer Pricing. International Journal of Finance (IJFIN) - ABDC Journal Quality List, 36(6), 150-181. https://ijfin.com/index.php/ijfn/article/view/IJFIN_36_06_008

[15] Malempati, M., & Rani, P. S. Autonomous AI Ecosystems for Seamless Digital Transactions: Exploring Neural Network-Enhanced Predictive Payment Models.

[16] Sondinti, K., & Reddy, L. (2024). Financial Optimization in the Automotive Industry: Leveraging Cloud-Driven Big Data and AI for Cost Reduction and Revenue Growth. Financial Optimization in the Automotive Industry: Leveraging Cloud-Driven Big Data and AI for Cost Reduction and Revenue Growth (December 17, 2024).

[17] Challa, K. (2024). Neural Networks in Inclusive Financial Systems: Generative AI for Bridging the Gap Between Technology and Socioeconomic Equity. MSW Management Journal, 34(2), 749-763.

[18] Ramanakar Reddy Danda, Z. Y., Mandala, G., & Maguluri, K. K. Smart Medicine: The Role of Artificial Intelligence and Machine Learning in Next-Generation Healthcare Innovation.

[19] Karthik Chava, Kanthety Sundeep Saradhi. (2024). Emerging Applications of Generative AI and Deep Neural Networks in Modern Pharmaceutical Supply Chains: A Focus on Automated Insights and Decision-Making. South Eastern European Journal of Public Health, 20–45. https://doi.org/10.70135/seejph.vi.4441

[20] Sriram, H. K. (2023). Harnessing AI Neural Networks and Generative AI for Advanced Customer Engagement: Insights into Loyalty Programs, Marketing Automation, and Real-Time Analytics. Educational Administration: Theory and Practice, 29(4), 4361-4374.

[21] AI-Powered Revenue Management and Monetization: A Data Engineering Framework for Scalable Billing Systems in the Digital Economy . (2024). MSW Management Journal, 34(2), 776-787.

[22] Krishna AzithTejaGanti, V., Senthilkumar, K. P., Robinson L, T., Karunakaran, S., Pandugula, C., & Khatana, K. (2024). Energy-Efficient Real-Time Hybrid Deep Learning Framework for Adaptive Iot Intrusion Detection with Scalable and Dynamic Threat Mitigation. KP and Robinson L, Thomas and Karunakaran, S. and Pandugula, Chandrashekar and Khatana, Kavita, Energy-Efficient Real-Time Hybrid Deep Learning Framework for Adaptive Iot Intrusion Detection with Scalable and Dynamic Threat Mitigation (November 15, 2024).

[23] Chaitran Chakilam, Dr. P.R. Sudha Rani. (2024). Designing AI-Powered Neural Networks for Real-Time Insurance Benefit Analysis and Financial Assistance Optimization in Healthcare Services. South Eastern European Journal of Public Health, 974–993. https://doi.org/10.70135/seejph.vi.4603

[24] Nampalli, R. C. R., & Adusupalli, B. (2024). Using Machine Learning for Predictive Freight Demand and Route Optimization in Road and Rail Logistics. Library of Progress-Library Science, Information Technology & Computer, 44(3).

[25] Intelligent Supply Chain Optimization: AI Driven Data Synchronization and Decision Making for Modern Logistics. (2024). MSW Management Journal, 34(2), 804-817.

[26] Syed, S., Jayalakshmi, S., Kumar Vankayalapati, R., Mandala, G., Yadav, O. P., & Yadav, A. K. (2024). A Robust and Scalable Deep Learning Framework for Real-Time Iot Intrusion Detection with Adaptive Energy Efficiency and Adversarial Resilience. Available at SSRN 5077791.

[27] R. Daruvuri, K. Patibandla, and P. Mannem, "Leveraging unsupervised learning for workload balancing and resource utilization in cloud architectures," International Research Journal of Modernization in Engineering Technology and Science, vol. 6, no. 10, pp. 1776-1784, 2024.

[28] Avinash Pamisetty. (2022). Enhancing Cloudnative Applications WITH Ai AND Ml: A Multicloud Strategy FOR Secure AND Scalable Business Operations. Migration Letters, 19(6), 1268–1284. Retrieved from https://migrationletters.com/index.php/ml/article/view/11696

[28] Somepalli, S. (2021). Dynamic Pricing and its Impact on the Utility Industry: Adoption and Benefits. Zenodo. https://doi.org/10.5281/ZENODO.14933981

[29] Nampalli, R. C. R., & Adusupalli, B. (2024). AI-Driven Neural Networks for Real-Time Passenger Flow Optimization in High-Speed Rail Networks. Nanotechnology Perceptions, 334-348.

[30] Chaitran Chakilam, Dr. Aaluri Seenu, (2024) Transformative Applications of AI and ML in Personalized Treatment Pathways: Enhancing Rare Disease Support Through Advanced Neural Networks. Frontiers in Health Informa 4032-4049

[31] Maguluri, K. K., Pandugula, C., & Yasmeen, Z. (2024). Neural Network Approaches for Real-Time Detection of Cardiovascular Abnormalities.

[32] Koppolu, H. K. R. Deep Learning and Agentic AI for Automated Payment Fraud Detection: Enhancing Merchant Services Through Predictive Intelligence.

[33] Sriram, H. K. (2022). AI Neural Networks In Credit Risk Assessment: Redefining Consumer Credit Monitoring And Fraud Protection Through Generative AI Techniques. Migration Letters, 19(6), 1017-1032.

[34] P. Mannem, R. Daruvuri, and K. K. Patibandla, "Leveraging Supervised Learning in Cloud Architectures for Automated Repetitive Tasks.," International Journal of Innovative Research in Science,Engineering and Technology, vol. 13, no. 10, pp. 18127–18136, Oct. 2024, doi: 10.15680/ijirset.2024.1311004.

[35] Chava, K. (2022). Redefining Pharmaceutical Distribution With AI-Infused Neural Networks: Generative AI Applications In Predictive Compliance And Operational Efficiency. Migration Letters, 19, 1905-1917.

[36] Yasmeen, Z., Machi, S., Maguluri, K. K., Mandala, G., & Reddy, R. (2024). Transforming Patient Outcomes: Cutting-Edge Applications of AI and ML in Predictive Healthcare. Transforming Patient Outcomes: Cutting-Edge Applications of AI and ML in Predictive Healthcare SEEJPH, 25, S1.

[37] Kishore Challa. (2024). Artificial Intelligence and Generative Neural Systems: Creating Smarter Customer Support Models for Digital Financial Services . Journal of Computational Analysis and Applications (JoCAAA), 33(08), 1828–1840. Retrieved from https://eudoxuspress.com/index.php/pub/article/view/1860

[38] Danda, R. R., Nampalli, R. C. R., Sondinti, L. R. K., Vankayalapati, R. K., Syed, S., Maguluri, K. K., & Yasmeen, Z. (2024). Harnessing Big Data and AI in Cloud-Powered Financial Decision-Making for Automotive and Healthcare Industries: A Comparative Analysis of Risk Management and Profit Optimization.

[39] Malempati, M. (2022). Machine Learning and Generative Neural Networks in Adaptive Risk Management: Pioneering Secure Financial Frameworks. Kurdish Studies. Green Publication. https://doi. org/10.53555/ks. v10i2, 3718.

[40] Pallav Kumar Kaulwar. (2022). The Role of Digital Transformation in Financial Audit and Assurance: Leveraging AI and Blockchain for Enhanced Transparency and Accuracy. Mathematical Statistician and Engineering Applications, 71(4), 16679–16695. Retrieved from https://philstat.org/index.php/MSEA/article/view/2959

[41] Nuka, S. T. (2024). The Future of AI Enabled Medical Device Engineering: Integrating Predictive Analytics, Regulatory Automation, and Intelligent Manufacturing. MSW Management Journal, 34(2), 731-748.

[42] Sambasiva Rao Suura. (2024). Artificial Intelligence and Machine Learning in Genomic Medicine: Redefining the Future of Precision Diagnostics. South Eastern European Journal of Public Health, 955–973. https://doi.org/10.70135/seejph.vi.4602

[43] Kannan, S. The Convergence of AI, Machine Learning, and Neural Networks in Precision Agriculture: Generative AI as a Catalyst for Future Food Systems.

[44] Srinivas Kalisetty, D. A. S. Leveraging Artificial Intelligence and Machine Learning for Predictive Bid Analysis in Supply Chain Management: A Data-Driven Approach to Optimize Procurement Strategies.

[45] The Future of Banking and Lending: Assessing the Impact of Digital Banking on Consumer Financial Behavior and Economic Inclusion. (2024). MSW Management Journal, 34(2), 731-748.

[46] Paleti, S. Transforming Money Transfers and Financial Inclusion: The Impact of AI-Powered Risk Mitigation and Deep Learning-Based Fraud Prevention in Cross-Border Transactions.

[47] Polineni, T. N. S., Kumar, A. S., Maguluri, K. K., Koli, V., Valiki, D., & Ravikanth, S. (2024). A Scalable and Robust Framework for Advanced Semi Supervised Learning Supporting Universal Applications. Available at SSRN 5080654.

[48] Vamsee Pamisetty. (2023). Optimizing Public Service Delivery through AI and ML Driven Predictive Analytics: A Case Study on Taxation, Unclaimed Property, and Vendor Services. International Journal of Finance (IJFIN) - ABDC Journal Quality List, 36(6), 124-149. https://ijfin.com/index.php/ijfn/article/view/IJFIN_36_06_007

[49] Komaragiri, V. B. (2024). Data-Driven Approaches to Battery Health Monitoring in Electric Vehicles Using Machine Learning. International Journal of Scientific Research and Management (IJSRM), 12(01), 1018-1037.

[50] Maguluri, K. K., Ganti, V. K. A. T., & Subhash, T. N. (2024). Advancing Patient Privacy in the Era of Artificial Intelligence: A Deep Learning Approach to Ensuring Compliance with HIPAA and Addressing Ethical Challenges in Healthcare Data Security. International Journal of Medical Toxicology & Legal Medicine, 27(5).

[51] Annapareddy, V. N. (2022). Innovative Aidriven Strategies For Seamless Integration Of Electric Vehicle Charging With Residential Solar Systems. Migration Letters, 19(6), 1221-1236.

[52] Vankayalapati, R. K., Yasmeen, Z., Bansal, A., Dileep, V., & Abhireddy, N. (2024, December). Advanced Fault Detection in Semiconductor Manufacturing Processes Using Improved AdaBoost RT Model. In 2024 9th International Conference on Communication and Electronics Systems (ICCES) (pp. 467-472). IEEE.

[53] Reddy, J. K. (2024). Leveraging Generative AI for Hyper Personalized Rewards and Benefits Programs: Analyzing Consumer Behavior in Financial Loyalty Systems. J. Electrical Systems, 20(11s), 3647-3657.

[54] K. Patibandla, R. Daruvuri, and P. Mannem, "Streamlining workload management in AI-driven cloud architectures: A comparative algorithmic approach," International Research Journal of Engineering and Technology, vol. 11, no. 11, pp. 113-121, 2024.

[55] Satyaveda Somepalli. (2024). Leveraging Technology and Customer Data to Conserve Resources in the Utility Industry: A Focus on Water and Gas Services. Journal of Scientific and Engineering Research. https://doi.org/10.5281/ZENODO.13884891

[56] Burugulla, J. K. R. (2022). The Role of Cloud Computing in Revolutionizing Business Banking Services: A Case Study on American Express's Digital Financial Ecosystem. Kurdish Studies. Green Publication. https://doi. org/10.53555/ks. v10i2, 3720.

[57] Annapareddy, V. N., & Sudha Rani, P. (2024). AI and ML Applications in RealTime Energy Monitoring and Optimization for Residential Solar Power Systems. Available at SSRN 5116062.

[58] Venkata Krishna Azith Teja Ganti ,Kiran Kumar Maguluri ,Dr. P.R. Sudha Rani (2024). Neural Network Applications in Understanding Neurodegenerative Disease Progression. Frontiers in HealthInformatics, 13 (8) 471-485

[59] Komaragiri, V. B., Edward, A., & Surabhi, S. N. R. D. Enhancing Ethernet Log Interpretation And Visualization.

[60] Pamisetty, V. (2023). Intelligent Financial Governance: The Role of AI and Machine Learning in Enhancing Fiscal Impact Analysis and Budget Forecasting for Government Entities. In Journal for ReAttach Therapy and Developmental Diversities. Green Publication. https://doi.org/10.53555/jrtdd.v6i10s(2).3480

[61] Ganti, V. K. A. T., Edward, A., Subhash, T. N., & Polineni, N. A. (2023). AI-Enhanced Chatbots for Real-Time Symptom Analysis and Triage in Telehealth Services.

[62] Daruvuri, R., Ravikumar, R., Mannem, P., & Aeniga, S. R. (2024). Augmenting Business Intelligence How AI and Data Engineering Elevate Power BI Analytics. International Journal of Innovative Research in Computer and Communication Engineering, 12(12), pp. 13012-13022.

[63] Challa, S. R. (2023). The Role of Artificial Intelligence in Wealth Advisory: Enhancing Personalized Investment Strategies Through DataDriven Decision Making. International Journal of Finance (IJFIN), 36(6), 26-46.

[64] Kalisetty, S., Pandugula, C., Sondinti, L. R. K., Mallesham, G., & Rani, P. S. (2024). AI-Driven Fraud Detection Systems: Enhancing Security in Card-Based Transactions Using Real-Time Analytics. Journal of Electrical Systems, 20, 1452-1464.

[65] Kannan, S. (2022). The Role Of AI And Machine Learning In Financial Services: A Neural Networkbased Framework For Predictive Analytics And Customercentric Innovations. Migration Letters, 19(6), 985-1000.

[66] Nuka, S. T. (2023). Generative AI for Procedural Efficiency in Interventional Radiology and Vascular Access: Automating Diagnostics and Enhancing Treatment Planning. Journal for ReAttach Therapy and Developmental Diversities. Green Publication. https://doi. org/10.53555/jrtdd. v6i10s (2), 3449.

[67] Malempati, M. (2022). AI Neural Network Architectures For Personalized Payment Systems: Exploring Machine Learning's Role In Real-Time Consumer Insights. Migration Letters, 19(S8), 1934-1948.

[68] Satyasree, K. P. N. V., & Kothpalli Sondinti, L. R. (2024). Mitigating Financial Fraud and Cybercrime in Financial Services with Security Protocols and Risk Management Strategies. Computer Fraud and Security, 2024(11).

[69] Challa, K. (2023). Transforming Travel Benefits through Generative AI: A Machine Learning Perspective on Enhancing Personalized Consumer Experiences. Educational Administration: Theory and Practice. Green Publication. https://doi. org/10.53555/kuey. v29i4, 9241.

[70] Somepalli, S. (2023). Power Up: Lessons Learned from World's Utility Landscape. Zenodo. https://doi.org/10.5281/ZENODO.14933958

[71] Chava, K., & Rani, D. P. S. (2023). Generative Neural Models in Healthcare Sampling: Leveraging AI-ML Synergies for Precision-Driven Solutions in Logistics and Fulfillment. Frontiers in Health Informa (6933-6952).

[72] Sriram, H. K., & Seenu, A. (2023). Generative AI-Driven Automation in Integrated Payment Solutions: Transforming Financial Transactions with Neural Network-Enabled Insights. International Journal of Finance (IJFIN), 36(6), 70-95.

[73] Shukla, A., Dubey, S., Nithya, P., Shankar, B., Vankayalapati, R. K., & Khatana, K. (2024). Edge-Optimized and Explainable Deep Learning Framework for Real-Time Intrusion Detection in Industrial Iot. Available at SSRN 5077557.