Generative AI-Powered Service Operating Systems: A Comprehensive Study of Neural Network Applications for Intelligent Data Management and Service Optimization

1. Venkata Bhardwaj Komaragiri, Lead Data Engineer, Ciena, Maryland,
ORCID ID : 0009-0002-4530-3075

Abstract

This paper provides a comprehensive study on generative AI-powered service operating systems—a new vision of advanced data management and service optimization that can relieve the complex understanding and long-term development of intelligent data analysis and information service optimization. To relieve such high complexity and mitigate the long-term development of intelligent data analysis and information service optimization, we apply the latest neural network models to conduct underlying data management services, including AI-augmented data search and exploration, AI-augmented data extraction, AI-augmented data cleansing and monitoring, and AI-augmented data analysis and prediction; and propose a group of advanced service distribution and real-time integration optimization services, including AI-augmented data retrieval optimization, AI-augmented service fusion optimization, AI-augmented service prediction, and AI-augmented service feedback control. Particularly, we adopt the recurrent neural network to implement advanced short-data-series services and conduct financial/categorical attribute imputation as an example to demonstrate the conducting process and noise control effect of the proposed tools.

Keywords: Generative AI, Service Operating Systems, Data Management, Service Optimization, Neural Networks, AI-Augmented Data Search, AI-Augmented Data Extraction, AI-Augmented Data Cleansing, AI-Augmented Data Monitoring, AI-augmented data Analysis, AI-augmented Prediction, Service Distribution, Real-Time Integration, AI-Augmented Retrieval Optimization, AI-Augmented Service Fusion, AI-Augmented Service Prediction, AI-Augmented Feedback Control, Recurrent Neural Network, Short-Data-Series Services, Financial Attribute Imputation.

1. Introduction

Recent advances in deep learning enabled timely access to large amounts of structured data stored in databases, spreadsheets, and other digital artifacts. This development has led to an increasing number of foundational research and development efforts in exploring new directions of deep learning applications to support a new generation of service operating systems that transform companies with an intelligence-based organizational capability. We focus on generative AI methods and discuss their novel applications in building generative AI-powered service operating systems in three categories: data preparation and management, AI algorithm selection and hyperparameter optimization, and system diagnostics and orchestration.

We present three comprehensive scenarios including predictive analysis, optimization, and KPI assignment using various state-of-the-art neural network models as the illustrative applications of these three categories. More importantly, we contribute to the service operations and generative AI literature by discussing the implications of the new AI approaches in transforming service operations in terms of productivity, capability, and value. The empirical findings suggest that operational flexibility is improved with the generative AI-powered service operating systems by lowering the entry barriers for new markets that enhance corporate ability to cope with environmental uncertainty, removing managerial biases by providing direct evidence of landmark policies and organizational strategies based on unbiased assessments, and increasing corporate capital appreciation rates.

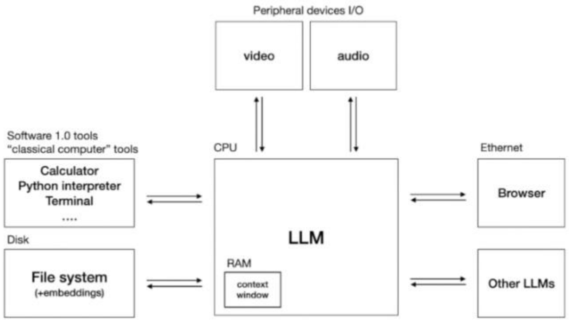

Fig 1 : AI as an Operating System is Shaping Our Digital Future

1.1. Background and Significance

Developing a new product or service is the dream of every entrepreneur. In practice, new businesses often fail to succeed in the beginning, and this is due to several reasons. As today's market environment changes rapidly and the dynamics of the world economy make this process even more difficult, the development of a service operating system that can adapt quickly is a great requirement. In today's technology, AI-powered service operating systems deliver unprecedented accuracy, timeliness, and reliability. These technologies complement or augment existing processes that were designed for human operation. With the help of AI-powered service operating systems, companies are not only efficient but also have capabilities that they never dreamed of. AI gives deep analytical and logical thinking abilities to large amounts of data, and thus services also enable companies to deliver complex, personalized customer experiences at scale in real-time.

Such systems make complicated tasks more manageable for workers who need to perform large amounts of work and allow them to handle customer challenges of the quantitative or qualitative categories based on available data. To provide data for artificial intelligence-based services, a cumulative database needs to be constructed, and the relationship between them should be well-defined. Within this setting, services adapted to today's technology are provided on the artificial intelligence-powered systems that must have accurate, agile, adaptable, decision-making, teaming, testing, nimbleness, privacy, and transparency characteristics. I believe this work is a comprehensive one that defines and explains fundamental issues of artificial intelligence-related services. Differently designed systems that are already in use can perform all communication, improvement, identification, problem-solving, intelligence, analytics, and valuable information services with their effective features. Ongoing discussions let me venture into my research. With the help of these technologies, companies are not only efficient but also have capabilities that they never dreamed of. AI gives deep analytical and logical thinking abilities to large amounts of data, and thus more personalized customer experiences at scale in real-time have enabled us. This study presents a comprehensive literature review of generative applications that are involved in many fields of artificial intelligence, especially in the field of machine learning. By doing so, this paper provides a general view of the rapidly changing field of artificial intelligence to industry professionals, researchers, members of educational institutions, and other interested stakeholders.

Equation 1 : Neural Network-Based Intelligent Data Processing

$$D_o = f(W D_i + B)$$

Where:

D_o = Processed data output

W = Weight matrix of the neural network

D_i = Input data features

B = Bias term

$f(\cdot)$ = Activation function (ReLU, Sigmoid)

1.2. Research Objectives

To develop a neoteric theory of Generative AI-Powered Service Operating Systems and establish a profound notion about Generative AI Service Management. This highlights the conceptual understanding of the Generative AI revolution and the new industrial age as the Service Industrial Internet of Things, while also expounding the significance of the study concerning Service Industrial Internet of Things, Generative AI, and service management. The central ideas of generative AI research are proposed. To demystify the true aspects behind Generative AI Service Management, the research objectives are presented. Additionally, innovative services that can be designed, created, customized, and shared by users on the generative AI engine with desirable, comprehensive, and various functioning services such as assisted autonomous differentiable software synthesis systems are also introduced.

1.3. Scope and Structure of the Paper

This paper focuses on a few important applications of generative AI in intelligent data management and data-driven service optimization areas and aims to illustrate how fully connected generative neural networks may serve as the core elements of next-generation AI-powered service operating systems. Our current work demonstrates that fully connected generative neural networks can greatly improve the efficiency of a broad range of AI-powered service operating systems, including, but not necessarily limited to, real-time big data analytics, blockchain-enabled decentralized marketplaces, AI-enabled customer service chatbots, as well as other versatile human-computer interaction and business process automation products. Since a general-purpose operating system is designed to deal with the management of both the hardware and the software of a computer platform, a general-purpose service operating system is designed to deal with the dynamic management of both the data and the business of a cloud-operated service platform.

The main structure of this paper is organized as follows. A high-level introduction to the data-driven business decision-making process powered by the general relay processing model is described in Section 2. The key elements of this model, including the context, the state, the physical event, the mental recognition, the mental context, and the signal-driven royalty, are explained in detail. A decade-long persistent data management continuum model of a business service platform is then presented in Section 3 to address the data-driven degradation of a business service platform that is commonly caused by generative adversarial data/pattern poisoning attacks. In Section 4, we look into several innovative application-specific generative neural network products that may enhance the performance of a service operating system and lead to new AI-powered services and introduce such AI-powered service operating systems as real-time big data processing pipelines, blockchain-enabled on-demand marketplaces, AI-enhanced human service agents, universal conversational AI, and service-aware employee recruitment tools to fully illustrate the outstanding utilization of fully connected VAE.

2. Fundamentals of Generative AI

Generative AI refers to the development of platforms that create, synthesize, or generate new content that resembles human cognitive intelligence, creativity, and innovation through simulating human intelligence processes such as visual and linguistic understanding, perceptual learning, information processing, and knowledge representation. Generative AI systems process, transform, distill, produce, and generate new generative content of data through neural network technology including convolutional neural networks, transformer blocks, generative adversarial networks, recurrent neural networks, as well as other neural architecture models that are specifically designed for generative processes such as Long Short-Term Memory, Boltzmann machines, powerful discriminator networks, and auto-encoding variations. Generative AI can generate solutions of single modality, multimedia such as image, audio, and video, and cross modalities such as text-to-image generation, text-to-generate audio, and generative text presentations. Generative AI can use objects and categories in a wide range of applications such as prose writing and storytelling, high-dimension and multiple matching, conversational systems and chatbots, automatic labeling, music composition, lyric discovery, programming, automatic image painting tools, data generation and data enhancement tools, web theme image design, effects filter, feature learning, concept design, simulation training and algorithmic thinking, digital map navigation, virtual simulation planning, object recognition and optical character recognition, medical image diagnostic improvement, graphical terrain simplification, product image rendering conversion, virtual reality, augmented reality, as well as on data observation and computer vision.

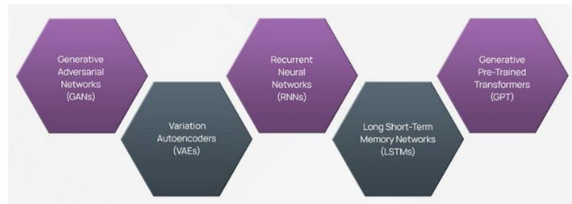

Fig 2 : Understanding Generative AI

2.1. Overview of Artificial Intelligence

Artificial intelligence focuses on the creation of machines or systems that can adapt and develop their thinking, learning, and problem-solving skills. These artificial systems are expected to achieve specific complex goals with precision, exhibiting characteristics typical of human cognition, such as perception, attention, pattern and image recognition, language understanding, reasoning, problem-solving, decision-making, intuition, learning, planning, self-improvement, and creativity. In the course of realizing these goals, the selection and implementation of methods enabling technologies to support such goals are diverse and broad. Cognitive science, philosophy, logic, mathematics, psychology, control theory, operations research, computer science, linguistics, economics, communication and signal processing, computational neuroscience, and statistical machine learning are some of the disciplines that have long been studied and have served as the foundation.

Even though the size and complexity of the problems that can be solved by AI seem to possess little boundary after the rapid development in AI algorithms and growing computing power in the past decade, no comprehensive models capable of really simulating the operation of the human brain have been established, depending instead on the collective effort of the research fields. Artificial neural networks are inspired by the brain to create a network of digital neurons that allow machines or systems to develop practically useful capabilities. More precisely, neural networks are machine-learning models that mimic the interconnected processes observed in the human brain, adaptively learning and solving both linear and non-linear problems. A neural network can capture similarities and commonalities within the set of examples, resulting in the development of models capable of generalizing and extracting new information from this set, which makes the network user capable of automating or improving the decision-making process.

2.2. Generative Models in AI

A generative model is an unsupervised learning method that can generate new samples from a given input distribution. It differs from a discriminative model, which is a supervised learning method that features classification or prediction. Classical generative models such as restricted Boltzmann machines use the principle of maximum likelihood estimation when modeling. Recently, there has been a wide range of generative models through the emergence of deep learning. The most popular generative neural network models are the generative adversarial network and the variational autoencoder. The question that arises is why 'generative' neural network models can produce high-quality data.

Statisticians have set standards for models that have data to be explained, and they assess data quality based on the types of samples that the models provide. For a model to be considered reliable and to produce samples of high quality, it should be capable of modeling visible input data. Neural network models have enough capacity to fit data, thus being able to produce high-quality data samples. Consequently, by default, many neural network models are generative models that can provide samples. This contrasts with discriminative models that learn to output a conditional distribution, which requires an input trigger.

2.3. Neural Networks and Deep Learning

Artificial intelligence (AI) is the most important engine of the Fourth Industrial Revolution. Its main paradigm, deep learning, was responsible for many breakthroughs in the fields of computer vision, speech recognition, advanced natural language processing, machine translation, speech synthesis, and so on. Deep learning is also called multi-layer neural network learning or representation learning. It is called "deep" learning because it makes use of multiple layers of neural networks, a friend for AI modeling.

Multi-layer (deep) learning applications using feedforward deep learning neural networks are often diverse choices for business analytics, especially for classification: extremely large-scale online supervised anomaly detection for critical product inspections, extremely large-scale complex decision-making with massive multi-category uncertainties, and complicated multi-type multi-dimensional uncertainties. Its applicability is found through an experiment on a Cold War game: Chess.

Although no optimality of deep learning for modeling real industrial activities is claimed, many current business analytic machine learning applications use deep learning. Its flexibility in approximate modeling of proprietary service-operating systems induces professional interests, and the choice of implementing applications using deep learning. In this paper, we analyze in detail a few real business cases implemented with deep learning and highlight its unique qualities and novelty in problem-solving with deep learning.

3. Service Operating Systems

The ability of current artificial intelligence technologies is often limited by predefined evaluation metrics and handcrafted model structures. While driving a boom in vast neural network models for benchmark tasks, improving the generality of AI applications is, however, deeply challenging. Domain-specific intelligent systems further face obstacles such as ill-defined environments, inconsistent requirements, overly implicit demands, and non-reusable specialized modules. To break through these limits with an open problem-solving strategy, we attempt to introduce AI-powered operating systems capable of service management and intelligent meta-learning to develop the underlying neural network techniques. We hope to sustain continuous and automated improvement in areas such as the model formulation environment, the experiment pipeline, the training framework, the predictive performance, and cooperative sociality. This technique necessitates a comprehensive and introspective methodology with applications throughout various industries. Consequently, we propose a systematic study addressing generative AI-powered service operating systems by establishing the generic definitions and unified frameworks for neural network use in core solution inference, meta-learning support, and model-integrated deployment.

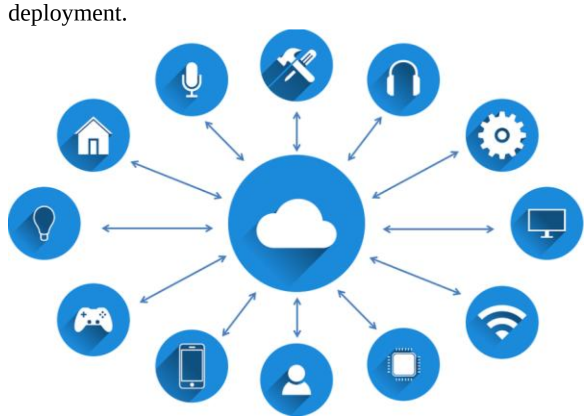

Fig 3 : Machine Learning Operating System

A service operating system routes the input queries into solution selection through various procedural processes within the underlying service provider; it is implemented with a service approach in the data control mechanism, the intelligent inference engine, and the model-integrated workflows. In a generative mode, the involved neural network service providers predict or synthesize the offered services, the demand routes, or the necessary data. These intelligent data generators, adaptive data consumers, and expressive data transformers produce the target AI-powered modeling, features, evaluation, utilization, and interpretation, with the capability of extensive tellable and train-less taskful extensions. This discussion aims to touch upon three key aspects of the neural network application, encompassing solution inferences, meta-learning supports, and model-integrated deployments, and to solicit attention from various highly developed service industries. Through a diversity of modeling studies, we elucidate required data management and service optimization factors in multiple sectors and introduce computable transformation functions and pre- and real-time supervision education techniques that are specially tailored for the involved operating problem-solving systems.

3.1. Definition and Components

The service operating system (S-OS) is defined as a software system comprising a diverse range of service applications operating on varying data, IT, and network resources, workflow business logic, and coordinating control, to deliver highly flexible, highly personalized, and multiple desired capabilities for the end customers in an efficient resource utilization way. The AI-powered S-OS is focused on AI-meaning-based software applications and their knowledge management tools. It maps symbol structure and knowledge meaning into the neural network vector structure, builds the deep lookup table in the neural network forms, and enables connection learning and knowledge meaning reasoning, with intensive AI learning training and reasoning. S-OS is unique in comparison with general-purpose operating systems or specific enterprise service management. They abstract the hardware and provide the basic functions. Users can run the service applications when they have the hardware, OS, and service applications. Enterprise service management is focused on the systems operated by a specific enterprise company. It can control and manage the company's workflows, resources, and operations. However, it primarily operates on structured data, and fixed capabilities, and is limited to the company operation. It is different from the service management of large-scale data center operators or internet service providers, which provide outsourced services to many different companies. In the data center, highly dynamic operation is required, together with high-level security and control, and upper-level aggregated capabilities for the dynamic customer-demand service creation, modifications, and operations. With the fast-growing requirements of the service from the cloud, mobile, IoT, and the complicated inter/intra interactions between the services, users, and many different kinds of resources, people will expect high-quality S-OS for better satisfaction. They expect one software with five key components to achieve the goal: personalized, efficient, easy, secure, and reliable.

3.2. Evolution and Current Trends

Neural networks mimic the human brain's structure through multilayer abstract information processing. Compared with rule-based machines, pattern mapping rule machines, and random stimulus-response machines, neural networks demonstrate a greater ability to abstract helpful low-scale features from huge, complex data sets to comprehend the current situation, thereby enabling successful prediction and decision support, which aids growth, power consumption, time cost, primary industries, and life quality optimization in the service industry. Over the past several years, data mining has regularly been replaced with deep learning-supported machine learning, enabling improved data processing, decision-making, service quality improvements, and operational cost concerns. By properly training and operating increasingly large neural networks with deep layers of neural processing of different Bayesian complexity and integrity, the classical theoretical maximum neural network performance limit of subject matter perception and prediction can be gradually approached. Attracting increased attention from various research fields and service industry actors, NLP-related research areas are:
1. training data.

Equation 2 : AI-Driven Service Optimization

$$S_{opt} = \arg\max \sum U(D_o, R)$$

Where:

S_{opt} = Optimized service strategy

$U(D_o, R)$ = Utility function of data output

D_o = Processed data output

R = Resource constraints

3.3. Challenges and Opportunities

Important potential constraints for the development of such DMTN services are the biases and poor decisions that harmful or unfair representation and ambiguous reasoning within the context and extent of the data could impart. This subset of challenges includes privacy and security breaches, adherence to ethical guidelines and regulations, reliable abstraction of underlying data representation, and convenient access and control over the hidden models and the derived data. Quality improvements in the input and output data and enhanced visual representation could lead to better management of the final output. It follows that examining the service operations could lead to a better understanding of the information, which could foster more reliable accreditation practices and enable feed-forward innovation. At the same time, it is important to account for the limitations in automation, to design the services under the presence of human-in-the-loop supervision, and to balance the AI-implemented decisions with heuristics and human expertise.

4. Applications of Neural Networks in Data Management

The processing of data is at the heart of data management. Enterprises today have data silos with specialized support for each type of data. What enterprises lack is a unifying infrastructure to deal with mixed data types alongside business process logic, operations data, and more. There is a lack of enterprise support for rapid intelligent packaging and usage of the data, which can be used by AI packages to drive many different AI applications. With that said, the use of AI and ANNs has been instrumental in several aspects of data management. This section provides the landscape of applications made by neural networks in data management. It includes a wide variety of different classes of AI technologies for different classes of AI problems. Most of the world's literature and research on AI techniques focus exclusively on statistical packages that are components of narrow AI and ML packages. The AI discussed has evolved to utilize most of the tools in the computer science toolbox and to integrate as many as possible into a general-purpose problem-solving system, but the intelligence that neural networks exhibit is more general-purpose than what can be provided one single class at a time by narrow AI and ML. Its various forms are probably the most general-purpose problem-solving support tools in the toolbox. They can provide general-purpose problem-solving support to fill in the gaps in narrow AI and ML intelligent applications and services created with ML. Collectors will not be able to use enterprise cross-system package end-user support functions and will have to be AI expert data scientists to fully benefit from them.

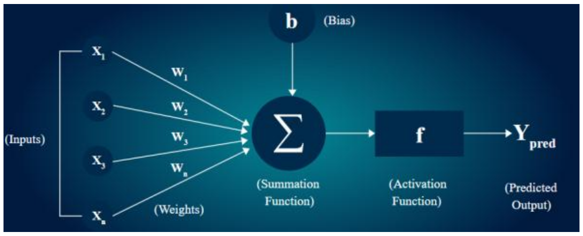

Fig 4 : Neural networks Architecture, applications, case

4.1. Data Preprocessing and Cleaning

The reliability of trained models is highly dependent on the quality and quantity of the training data. Think of the model as a student in a classroom. Preprocessing and cleaning are the processes that make the students ready for classes. The students are from different family backgrounds. Some are intellectually rich and some are not. In this experiment called supervised learning, all the students will answer the same question. Of course, students from rich families can answer the question better than others. We preprocess the students to help them have more equal economic conditions through disguising and, when necessary, we clean the students' houses by filling in missing data, addressing extreme values, and balancing the data. It will severely weaken the reliability and consistency of the trained model if the data is not carefully processed or if unqualified data is used to train the model. Using data that do not meet the prerequisite conditions to train machine learning models not only cannot help achieve the intended results but also brings negative effects on many dimensions. Most importantly, using low-quality data can easily lead to a crisis of confidence in artificial intelligence technology throughout society, rendering the so-called data-driven decision-making extremely immature and highly unreliable.

We present eight common preprocessing steps involved in machine learning model training. The first step discards redundant data, which is completely dependent on another one. If a certain feature represents the median age when another feature represents the average age, this feature is a good example of redundant data and can be discarded. However, if all values of a feature are missing or nearly missing, this feature should be used carefully during preprocessing or discarded if necessary. The second step is the filling of missing data. When considering the filling of missing data, it is necessary to observe the filling status of all the features before making a decision, given that this decision may create correlations between features. For continuous numeric data, a common method to fill missing data is to use the feature's mean value because algorithms like the decision tree are more likely to imitate the trend of the data if the average value representation is used.

4.2. Data Classification and Clustering

Task 1, as the initial stage focusing on data preprocessing, generally focuses on data classification and clustering to classify data into common classes to facilitate subsequent tasks. Data classification and clustering are widely adopted to identify unique subpopulations, patterns, and outlier events. Specifically, there are 6 subgroups. In comparison to rule-based methods, neural network-based methods are data-driven in application upon column classification and entire record classification to identify data nature, and further data feature classification and feature detection. Task 2 involves data cleansing, specifically to detect, fix, and remove noise or errors from a dataset and improve data quality. A total of 2 subgroups were extracted. Current studies apply a simple preprocessing pipeline workflow with input from experimental data-generating layers to a final data file-producing layer, to sequentially accomplish column error detection and correction within the batch or streaming mode. Although the relative sample size is still quite low when compared with data cleaning tasks in the field of traditional data management.

Based on our study, researchers fall within this application sub-cost category, which is mostly centered on data classification. Data classification, addressing the problem of identifying the unique subpopulations within the data in a peer-building block type of layer pipeline, well aligns with the core of generative AI. Development is epitomized by deep generative networks which have a core that resembles two well-founded deep learning concepts—feature representation acquisition and supervised feature representation training—offering efficient distribution-free data representation for downstream statistical inference simulations. These data classification contributions from generative AI not only can help other components within the data and service operating system to clamp or frame their contemporaneous pros and cons, but also are the cornerstone for the entire generative AI-powered data management and service optimization system paradigm. Moreover, practically, domain-aware feature-driven data domain description information may improve data quality dramatically.

4.3. Anomaly Detection

Anomaly detection is an active research field with extensive applications used for intrusion detection in security systems, fault diagnosis in industrial manufacturing, and fraud detection in finance systems. The basic idea is to identify the data points that deviate from seemingly regular patterns of data behavior and alert accordingly. Unlike these traditional solutions that rely on manually crafted features or are prone to adversarial attacks, in an increasing number of applications, anomaly detection can be solved by directly training deep neural networks. Practically, deep generative models can embrace several flexibilities over traditional solutions and have shown promising performance, especially when data are high-dimensional but not very large. In addition, the generative ability of deep models to synthesize data is an added advantage.

Anomaly detection can be solved by designing classification models and flagging the observations as 'anomaly' or 'normal'. Specifically, training a point-by-point classifier is not likely to achieve good results in the generative context because the classifier will perform poorly on the anomalies that never appear in the training data. We can use a generative model to estimate the distribution of what is 'normal'. Any data points that are poorly explained given that distribution—e.g., noisy reconstructions from an autoencoder—are interpreted as being anomalies. The generative models used in the context of anomaly detection can be several standard autoencoders or Variational Autoencoders. Furthermore, a VAE-GAN structure, i.e., training a VAE to regularize the GAN during training, is proposed as a suitable anomaly detector for real-world problems when the likelihood is not a good fit for the discriminator. The hybrid model has advantages over both unsupervised networks and can replace the time-consuming example collection and labeling required for unsupervised transfer learning and diminish the model limitations. Additionally, the classifier is designed by introducing KL loss into G, reducing the inconsistency and susceptibility of the general autoencoder, to overcome the imbalance of anomalies and normal data, showing the contribution in value of the classifiers produced by hybrid models compared to unsupervised networks. It is also recommended to start by fitting an easy-to-learn sampler and then switch to a good generative model for generating data.

5. Service Optimization with Neural Networks

The optimization of the management of demand patterns, resources, and data assets of intelligent data service systems driven by applications of traditional analytics, data mining, and decision support algorithms may only achieve or converge to a degree significantly below the performance goal of such system operations, due to the conflation between demand forecasting and related data and resource management, forecasting myopia problems of existing algorithms, and insufficient performance of the business models, decisions, and the resulting client-facing service. This paper investigates neural network applications for optimizing service systems in various areas of healthcare, including the optimization of mobile primary care service zone networks, appointment scheduling of imaging diagnostic centers, and staff scheduling of pediatric care services.

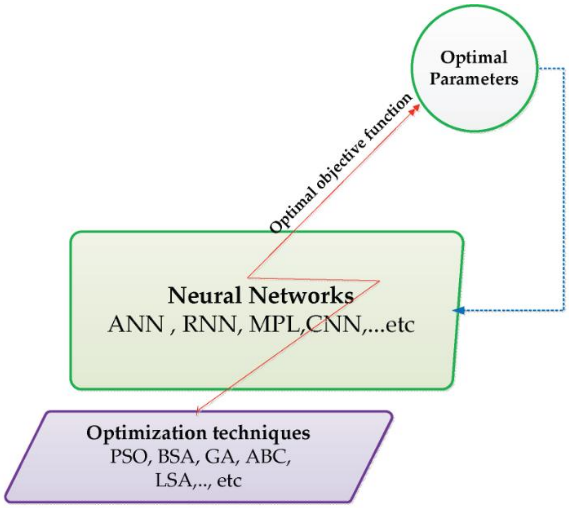

Fig 5 : Artificial Neural Networks Based Optimization Techniques

The verified effectiveness and median to high accuracy of such applications prove the benefits of replacing traditional forecasting of separate demand patterns, medical resource requirements, and operational indicators with embedding services to obtain the dependent order of the long-term demand scenarios or operations. The design instructions and emerging methodologies facilitate the subsequent development and deployment of generative, high-performance, intelligent service models powered by applications of traditional forecasting analytics, optimization algorithms, and other high-accuracy, larger general neural network modules.

This paper investigates by executing different experiments and assessment architectures, which input parameters, those operational patterns or future states, obtained through extensive services and deep neural network training and generation, concerning certain features and functions of each healthcare service. The role of selections in our experiments has been verified by calculating the performance of the experience associated with or without using those input parameters, as well as by observing different levels of internalized inventory of knowledge transferred into various constituents of models inside the network architectures. Specifically, we have trained a service planning module with policies that concatenate the original neural network architectures. With those results achieved or learned by planning the module, we continue to train and test densely connected neural networks, heavily relying on certain rescaled versions of those results in practice. The experiments, under extensive training and verification architectures and results, lead to the design instructions or machine learning models, as well as suggestions for the development of neural network applications optimized for those intelligent data service systems. The material of this paper is to guide future research and big enterprises or policymakers who are interested in developing AI technologies to improve service systems with deep learning.

5.1. Predictive Maintenance

Predictive maintenance (PdM) has become a significant feature in preventing and dealing with failures and unforeseen issues. A series of predictive maintenance may also involve predicting the amount of remaining useful life (RUL) for intelligent part management and service, as well as ensuring minimal operational costs for the stable operation of systems. Predictive maintenance may help users prevent unexpected equipment breakdowns, improve equipment uptime, and help maintenance staff plan ahead of time. Applications can be introduced to part and service lifecycle management, for example, in industrial robots. Toward the 4th Industrial Revolution and smart manufacturing, few studies have used deep learning techniques to predict RUL in the domain of predictive maintenance.

The key component is the model for monitoring the remaining useful life system, which includes the normalization of input data and the procedure to detect and recover predictive outliers. Based on historical weather and maintenance data, deep learning through neural networks involving the autoencoder and recurrent neural networks is also used to predict the remaining life of machines. In addition, an optimized model based on a k-D tree and synthetic data is proposed to improve prediction accuracy in predicting the length of remaining useful life through long short-term memory.

5.2. Resource Allocation

Resource allocation and capacity planning are vital functions in many IT services such as cloud reservation systems, call centers, online food delivery services, retail fulfillment, package delivery services, and warehouse management, especially for services with significant marginal IT costs and service operation risks. Resource allocation requires the development of an analytics system to forecast information from data and service requests such as demand, time of arrival, duration, and urgency specific to the GDP situation. Good predictions can offer many benefits: customers can be proactively informed of price increases when the allocation of resources is close to capacity, and the service provider can also use the analytics to assess future operation risks associated with an insufficient surge in capacity, which may affect the performance of the service and the reputation of the provider negatively.

Resource allocation strategies can be classified into different classes, depending on the various GDP factors and the service request characteristics. For end users, the methods may include the optimal bid, sharing option, non-intrusive time, non-intrusive power, and the profile. For instance, the optimal bid means the productive users assign an optimal full budget for all tasks, allowing productive users to explore the potential improvements associated with an increase in budget beyond a sharing option. The non-intrusive time strategy aims to protect the activities of productive users by not interfering at the most active hours or by allocating unavailable service at a time window that does not overlap. These methods offer different levels of user experiences and need effective solutions involving menu price planning, scheduling, service decomposition, and re-composition processes as well as formulating suitable incentive mechanisms. For small business owners, on the other hand, who stay at home and need to maintain a predefined level of operation, methods such as forgoing tasks and profile strategies might be useful.

The existing literature has been focused mainly on capacity planning for efficient service levels with applications in industries. Different machine learning models including graphical models, deep learning models, variable sequence length forecasting models, loss elastic net regularized regression models, and deep reinforcement learning models were applied to time series demand forecasting and customer choice modeling problems in various contexts, including online ERP and S&OP management systems for cold chain logistics service providers, dynamic pricing in the airline industry, personalized recommendation systems, warehouse labor staffing, and revenue management. All of the models have a common goal, which is to increase the minimum profitability requirement while maintaining acceptable customer service levels, safety, and operating quality for both the people and pets of the GDP community.

5.3. Dynamic Pricing Strategies

Dynamic pricing, a sophisticated form of revenue management that has been widely adopted, is a pricing strategy in which the product or service price is not fixed but varies over time as a function of demand and/or supply conditions to maximize revenue. Over the years, researchers have proposed various methodologies, including pricing controls, rule-based and optimization approaches, to model and optimize the dynamic pricing problem under the circumstances of perfect and/or imperfect information. Nevertheless, high fluctuations in consumer behavior during the purchasing process have led to active research on dynamic pricing. It is observed that dynamic pricing strategies exhibit the potential to increase the future return on a sale by promoting delays in retrieved orders for pricing changes.

Currently, dynamic pricing strategies, such as demand forecasting, price discrimination, price optimization, and buy-back contracts, have found numerous applications in various industries, including the electric power industry, telecommunications, retail, and businesses in the sharing economy. Based on the perception capability and actions of the service provider, prior research has been leveraged in the introduction of dynamic pricing schemes for network services, content sharing, and scheduling on distributed clouds. However, under stringent computing or service level constraints, known approaches demand high computational efforts or generate unsatisfactory solutions. Therefore, current proposals are not suitable for practical use. In this research, deep reinforcement learning, the agent-based learning paradigm, is applied to the service operating system to systematically analyze its potential capability to cope with complex simulations of dynamic pricing strategies and propose novel scenarios that have not been addressed in the past.

6. Challenges and Future Directions

In this section, we provide a discussion of challenges and future research directions for generative AI-powered service operating systems. 6.1. Challenges SLAs on blockchain deployment. It is important to guarantee the data and the AI services negotiated by SLAs on the decentralized marketplace. Their execution of smart contracts becomes protozoological. Real-time SLA adaptation. SLA changes must be done quickly without violating the guarantees of the service. However, current state-of-the-practice approaches to SLA adaptation are complex to adapt. Adaptive data-driven service composition. Service-port modeling as task distribution to achieve guaranteed results is currently unused as a solution to adapt the service's features to the large volume of customer requirements in the AI data marketplace scenario. Support for big data and real-time data management. New architectures for big data and business transactions must be designed to support scalability and high-performance requirements with emerging AI application services. Data federation behavior composition. Generated data shows on federated databases how to ensure the consistency of the results individually returned through rapid negotiations without data exchange. MLaaS instances must enforce fair data use requests but support access to opaque and encrypted models, feature-transforming models, and fully transparent data and feature transformation.

Ontology vs. machine learning guarding the data pipeline. The evolution of the data pipeline from data production to commercial data production may result in drifts of the concepts in representation ranges. The capabilities of human expertise to resolve semantic representation breaches and machine learning algorithms to look for predictions to classify and discover the expression can reverse the quality of the data prediction capabilities. A binding contract automation research improvement. The goal of our future work would be to handle the binding market relationships of providers integrated with semi-centralized management solutions to maximize decentralized services in the ecosystem. SLA leverage data model, policies, and execution workload allow application developers to know the SLA required to create new, business-critical, and market-quality machine learning services. In turn, this information could be used by service providers to analyze and approve new service offerings and financial models.

6.2. Future work creating effective AI service operating systems can only result from meetings: this is why new research activities and scope will inform a more mature business ecosystem.

Computational model procurement. The SLA research backlog is growing. All of these require custom, data-intensive, backend-configurable APIs. It must confirm that the existing models can be used in all cases, particularly adapting the inputs and outputs of the business case. Advance the fairness of transparency and certification of smart contracts as SO BE. And some certifiable technical fields, particularly smart thresholds, by facilitating some tests like global. The growth of business interest may have benefited the development of a secure runtime for the business enterprise. The development of secure smart contracts can also arise by giving financial implications, the costs. Protocol for business security and malicious attacks. They can all be concealed from the buyer or others in the financial model or the sender's location. Therefore, there is a need to design protocols based on secure hardware and an attack resembling them, including but not limited to the model of cryptography used in them. Improve buyer and seller identification. A model specifies complex high-quality behavior and real-time learning that is less impressive when used by the purchaser in distributed functions. This is due to the design choices of protocols based on secure hardware and encryption used by other vendors. Finally, support and redirect request outputs all require a model or a probability approach in identifying authorization by the seller.

6.1. Ethical Considerations

1. For every technology, there is an ethical dimension, and AI is no exception. Indeed, for AI, independently of its power, the ethical dimension is key, given its potential consequences on the daily life of people: for instance, in self-driving cars or cancer diagnosis. The proposed principles could be seen as the basis for an ethical framework dealing with ethical issues in AI. These principles originate from extensive discussions with citizens, technology experts, business leaders, policy stakeholders, and policymakers around a value charter assembled using a survey and four workshops. Collectively examining opportunities and risks and considering the elaboration of human-centric principles, these principles aim to guide the policy framework of AI while promoting the values of democracy, equality, a fair market economy, and social protection.

In this respect, a collection of resources is being assembled that aim to maintain portals to the AI ethics discussion. This collection contains an extensive community of organizations generating guidelines. The organization is a multi-stakeholder group that includes civil society groups, companies, researchers, and governments, striving to ensure that AI serves the needs of society. Users will find an extensive range of AI ethics resources, including reports, frameworks, and others.

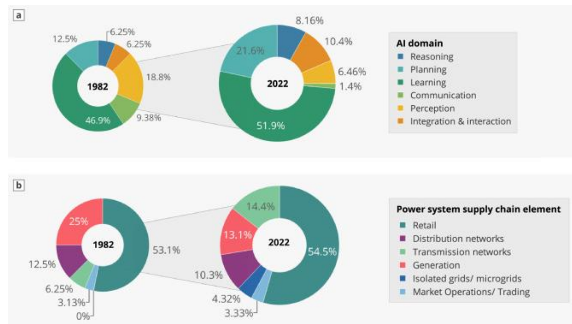

Fig 6 : Artificial Intelligence Applied to Power Systems

6.2. Limitations and Potential Risks

Despite the many advances and rapid deployment of generative models in substitution of traditional service optimization methods, limitations and potential risks are present that need to be kept in mind. One major limitation is that the acknowledged correlation between the generative approach and real-world environments is constructed by the neural network trained over historical data. Without enough practical monitoring supported by human expertise, the outcome of the generation process — in particular, the part of the generated dataset that is not cross-validated for common features of the real-world datasets — cannot be trusted. Further potential risks are related to the rapidly changing and overly automated environments. A multidisciplinary system that features cybersecurity, data ethics, human behavioral guidelines, and practical law is required to guide how generative models could be implemented.

Another potential major risk is that once the use of generative models becomes mainstream, the performance of simple discriminative neural networks for any task may be fundamentally limited, driving domain experts who have provided unbiased domain knowledge toward generative models over time due to financial interests. This is a potential negative path to further develop data science outcomes in the future. Consequently, the mere utilization of generative models is not the most innovative part of the proposed framework. Our unique contribution lies in the comprehensive framework that incorporates generative models for generating data, inferring indicators, and facilitating model interpretability and causality; and the fact that we study multiple aspects of system behavior, including multiple objectives and cycles, and draw implications for feature management in modeling and the real world.

6.3. Future Research Areas

In this section, we collect significant future research opportunities inherent to the generative AI-powered service OS. The subsequent section outlines limitations and challenges. We strongly believe that by systematically addressing these opportunities, researchers and trailblazers could equip this critical technology with comprehensive capabilities for handling challenging real-world service workloads.

Equation 3 : Real-Time Adaptive System Performance

$$P_t = \frac{\sum(D_o \cdot A_t)}{T}$$

Where:

P_t = Performance score at time t

D_o = Processed data output

A_t = AI-driven adjustment factor

T = Total time intervals analyzed

7. Conclusion

The urgent demand for generating a new kind of service that offers a more intelligent, frictionless, zero-trust, and seamless user-cloud computing experience, with high optimization speed, high configuration flexibility, high fault tolerance, high automation, high failure reliability, high privacy-security accountability, high real-time accuracy, high interactivity, high privacy-security usability, high cost-sensitive privacy-security, and high resource utilization efficiency, has promoted the industry's interest to invest in a multi-trillion-dollar market in service-oriented computing. Service operating systems aim to develop a general service model to provide artificial, continuous, effective, and scalable AI-powered assistant services to satisfy today's and future intelligent data management and service optimization system applications' demand, with high efficiency, high accessibility, high utility, and high adaptability, and have attracted much attention from the research community in various domains. In this comprehensive review, we rigorously and collectively review research in this direction and present a taxonomy to categorize different approaches. In the end, we summarize the learning tasks and training data of existing methods, the evaluation/design principles of different applications, and identify some potential directions for future research. The objective of this review was to highlight several core emerging research directions that focus on generative AI-powered service operating systems that rely on a general service model to provide artificial, continuous, effective, and scalable AI-powered assistant services to satisfy and complement different application demands of intelligent data management and service optimization efficiently, accurately, and effectively, without introducing excessive privacy-security risks or increasing economic costs. We expect that with the rapid development of AI technology, the existing research will drive strategies towards the effective development of generative AI-powered service operating systems.

7.1. Summary of Key Findings

The vision of AI-powered service operating systems has attracted a great deal of attention from both academia and industry. Key digital service platforms are being augmented and upgraded by generative systems that deliver innovative solutions through novel R&D in AI, machine learning, and related areas. A comprehensive survey of representative AI applications for enabling intelligent behavior in service operation and management demonstrates up-to-date interests and trends, as they effectively address challenges concerning veracity-originated issues in data and systems, services, and user interaction in the digital service landscape. Based on the comprehensive picture of AI techniques applied for intelligent data management and service optimization, challenges and opportunities for future development are presented, and open research issues and future directions are proposed for AI systems to sustainably adapt and evolve towards real-time intelligence with automated decision-making and analytics-aware real-time service systems for diminishing veracity, including AI for the physical service systems and AI-driven interactions with multiple service channels across realms. In this paper, we review AI applications as an enabler for intelligent capabilities in service operating systems. AI provides neural network-based solutions to complement service platforms with a wide variety of intelligent capabilities in terms of awareness, anticipation, adaptation, autonomous management, and active interventions, which thereby enhance service operations and user experiences. In summary, this work has helped consolidate the latest trends, service platforms, and techniques in AI-powered service systems and propose future research directions. The research trends discussed in this paper concern updating and upgrading the capabilities of service operating systems powered by AI technologies, thereby granting the system the capability of collecting and analyzing real-time data as autonomous operations run, to take immediate action in response to dynamic changes in the operational environment and deliver timely, optimal, and active assistance.

7.2. Implications and Recommendations for Practice

Our goals are to give an overview of generative AI-powered SDO systems currently available and being developed, explore the patterns those systems are built on and the characteristics of tasks they are designed for, identify the similarities and differences between the offered systems and the concept developed, explore the interrelations between the system types and the tasks. Several implications can be drawn from deploying the results of the research discussed above into practice, including the use of it as a guide and indication in the design, implementation, adaptation, and learning of neural service systems and the enhancement of service value production that such guides and indications bring about. A third important implication is the distinction between models and operational problems on the one hand and the specific form and structure of the content and boundary of the service that is under research. It is required to find this distinction since it narrows and sharpens the specifications of wants and ways in the design, diagnosis, development, learning, and understanding that such models and operational problems provide. The nature of SDO systems discussed above implies that service patterns bring their unique type of problems that can be studied and an approach developed to facilitate learning.

8. References

[1] Vaka, D. K. (2024). Enhancing Supplier Relationships: Critical Factors in Procurement Supplier Selection. In Journal of Artificial Intelligence, Machine Learning and Data Science (Vol. 2, Issue 1, pp. 229–233). United Research Forum. https://doi.org/10.51219/jaimld/dilip-kumar-vaka/74

[2] Ravi Kumar Vankayalapati , Chandrashekar Pandugula , Venkata Krishna Azith Teja Ganti , Ghatoth Mishra. (2022). AI-Powered Self-Healing Cloud Infrastructures: A Paradigm For Autonomous Fault Recovery. Migration Letters, 19(6), 1173–1187. Retrieved from https://migrationletters.com/index.php/ml/article/view/11498

[3] Syed, S. (2024). Enhancing School Bus Engine Performance: Predictive Maintenance and Analytics for Sustainable Fleet Operations. Library Progress International, 44(3), 17765-17775.

[4] Nampalli, R. C. R. (2024). AI-Enabled Rail Electrification and Sustainability: Optimizing Energy Usage with Deep Learning Models. Letters in High Energy Physics.

[5] Lekkala, S. (2024). Next-Gen Firewalls: Enhancing Cloud Security with Generative AI. In Journal of Artificial Intelligence & Cloud Computing (Vol. 3, Issue 4, pp. 1–9). Scientific Research and Community Ltd. https://doi.org/10.47363/jaicc/2024(3)404

[6] Manikanth Sarisa , Gagan Kumar Patra , Chandrababu Kuraku , Siddharth Konkimalla , Venkata Nagesh Boddapati. (2024). Stock Market Prediction Through AI: Analyzing Market Trends With Big Data Integration . Migration Letters, 21(4), 1846–1859. Retrieved from https://migrationletters.com/index.php/ml/article/view/11245

[7] Vaka, D. K. (2024). From Complexity to Simplicity: AI’s Route Optimization in Supply Chain Management. In Journal of Artificial Intelligence, Machine Learning and Data Science (Vol. 2, Issue 1, pp. 386–389). United Research Forum. https://doi.org/10.51219/jaimld/dilip-kumar-vaka/100

[8] Tulasi Naga Subhash Polineni , Kiran Kumar Maguluri , Zakera Yasmeen , Andrew Edward. (2022). AI-Driven Insights Into End-Of-Life Decision-Making: Ethical, Legal, And Clinical Perspectives On Leveraging Machine Learning To Improve Patient Autonomy And Palliative Care Outcomes. Migration Letters, 19(6), 1159–1172. Retrieved from https://migrationletters.com/index.php/ml/article/view/11497

[9] Shakir Syed. (2024). Planet 2050 and the Future of Manufacturing: Data-Driven Approaches to Sustainable Production in Large Vehicle Manufacturing Plants. Journal of Computational Analysis and Applications (JoCAAA), 33(08), 799–808. Retrieved from https://www.eudoxuspress.com/index.php/pub/article/view/1453

[10] Nampalli, R. C. R., & Adusupalli, B. (2024). Using Machine Learning for Predictive

Freight Demand and Route Optimization in Road and Rail Logistics. Library Progress International, 44(3), 17754-17764.

[11] Ramanakar Reddy Danda (2024) Financial Services in the Capital Goods Sector: Analyzing Financing Solutions for Equipment Acquisition. Library Progress International, 44(3), 25066-25075

[12] Chandrababu Kuraku, Shravan Kumar Rajaram, Hemanth Kumar Gollangi, Venkata Nagesh Boddapati, Gagan Kumar Patra (2024). Advanced Encryption Techniques in Biometric Payment Systems: A Big Data and AI Perspective. Library Progress International, 44(3), 2447-2458.

[13] Vaka, D. K. (2024). Integrating Inventory Management and Distribution: A Holistic Supply Chain Strategy. In the International Journal of Managing Value and Supply Chains (Vol. 15, Issue 2, pp. 13–23). Academy and Industry Research Collaboration Center (AIRCC). https://doi.org/10.5121/ijmvsc.2024.15202

[14] Vankayalapati, R. K., Sondinti, L. R., Kalisetty, S., & Valiki, S. (2023). Unifying Edge and Cloud Computing: A Framework for Distributed AI and Real-Time Processing. In Journal for ReAttach Therapy and Developmental Diversities. Green Publication. https://doi.org/10.53555/jrtdd.v6i9s(2).3348

[15] Syed, S. (2024). Sustainable Manufacturing Practices for Zero-Emission Vehicles: Analyzing the Role of Predictive Analytics in Achieving Carbon Neutrality. Utilitas Mathematica, 121, 333-351.

[16] 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.

[17] Ramanakar Reddy Danda, Valiki Dileep,(2024) Leveraging AI and Machine Learning for Enhanced Preventive Care and Chronic Disease Management in Health Insurance Plans. Frontiers in Health Informatics, 13 (3), 6878-6891

[18] Sanjay Ramdas Bauskar, Chandrakanth Rao Madhavaram, Eswar Prasad Galla, Janardhana Rao Sunkara, Hemanth Kumar Gollangi (2024) AI-Driven Phishing Email Detection: Leveraging Big Data Analytics for Enhanced Cybersecurity. Library Progress International, 44(3), 7211-7224.

[19] Dilip Kumar Vaka. (2019). Cloud-Driven Excellence: A Comprehensive Evaluation of SAP S/4HANA ERP. Journal of Scientific and Engineering Research. https://doi.org/10.5281/ZENODO.11219959

[20] Maguluri, K. K., Pandugula, C., Kalisetty, S., & Mallesham, G. (2022). Advancing Pain Medicine with AI and Neural Networks: Predictive Analytics and Personalized Treatment Plans for Chronic and Acute Pain Managements. Journal of Artificial Intelligence and Big Data, 2(1), 112–126. Retrieved from https://www.scipublications.com/journal/index.php/jaibd/article/view/1201

[21] Syed, S. (2024). Transforming Manufacturing Plants for Heavy Vehicles: How Data Analytics Supports Planet 2050's Sustainable Vision. Nanotechnology Perceptions, 20(6), 10-62441.

[22] Nampalli, R. C. R. (2024). Leveraging AI and Deep Learning for Predictive Rail Infrastructure Maintenance: Enhancing Safety and Reducing Downtime. International Journal of Engineering and Computer Science, 12(12), 26014–26027. https://doi.org/10.18535/ijecs/v12i12.4805

[23] Danda, R. R., Nishanth, A., Yasmeen, Z., & Kumar, K. (2024). AI and Deep Learning Techniques for Health Plan Satisfaction Analysis and Utilization Patterns in Group Policies. International Journal of Medical Toxicology & Legal Medicine, 27(2).

[24] Data Engineering Solutions: The Impact of AI and ML on ERP Systems and Supply Chain Management. (2024). In Nanotechnology Perceptions (Vol. 20, Issue S9).

Rotherham Press. https://doi.org/10.62441/nano-ntp.v20is9.47

[25] Vaka, D. K. (2020). Navigating Uncertainty: The Power of ‘Just in Time SAP for Supply Chain Dynamics. Journal of Technological Innovations, 1(2).

[26] Danda, R. R. (2024). Generative AI in Designing Family Health Plans: Balancing Personalized Coverage and Affordability. Utilitas Mathematica, 121, 316-332.

[27] Pandugula, C., Kalisetty, S., & Polineni, T. N. S. (2024). Omni-channel Retail: Leveraging Machine Learning for Personalized Customer Experiences and Transaction Optimization. Utilitas Mathematica, 121, 389-401.

[28] Syed, S. (2023). Shaping The Future Of Large-Scale Vehicle Manufacturing: Planet 2050 Initiatives And The Role Of Predictive Analytics. Nanotechnology Perceptions, 19(3), 103-116.

[29] Nampalli, R. C. R. (2023). Moderlizing AI Applications In Ticketing And Reservation Systems: Revolutionizing Passenger Transport Services. In Journal for ReAttach Therapy and Developmental Diversities. Green Publication. https://doi.org/10.53555/jrtdd.v6i10s(2).3280

[30] Malviya, R. K., Danda, R. R., Maguluri, K. K., & Kumar, B. V. (2024). Neuromorphic Computing: Advancing Energy-Efficient AI Systems through Brain-Inspired Architectures. Nanotechnology Perceptions, 1548-1564.

[31] Patra, G. K., Kuraku, C., Konkimalla, S., Boddapati, V. N., Sarisa, M. and Reddy, M. S. (2024) An Analysis and Prediction of Health Insurance Costs Using Machine Learning-Based Regressor Techniques . Journal of Data Analysis and Information Processing, 12, 581-596. doi: 10.4236/jdaip.2024.124031.

[32] Danda, R. R. (2024). Generative AI for Enhanced Engagement in Digital Wellness Programs: A Predictive Approach to Health Outcomes. Journal of Computational Analysis and Applications (JoCAAA), 33(08), 788-798.

[33] Kalisetty, S., Pandugula, C., & Mallesham, G. (2023). Leveraging Artificial Intelligence to Enhance Supply Chain Resilience: A Study of Predictive Analytics and Risk Mitigation Strategies. Journal of Artificial Intelligence and Big Data, 3(1), 29–45. Retrieved from https://www.scipublications.com/journal/index.php/jaibd/article/view/1202

[34] 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.

[35] Madhavaram, C. R., Sunkara, J. R., Kuraku, C., Galla, E. P., & Gollangi, H. K. (2024). The Future of Automotive Manufacturing: Integrating AI, ML, and Generative AI for Next-Gen Automatic Cars. In IMRJR (Vol. 1, Issue 1). Tejass Publishers. https://doi.org/10.17148/imrjr.2024.010103

[36] Danda, R. R. (2024). Using AI-Powered Analysis for Optimizing Prescription Drug Plans among Seniors: Trends and Future Directions. Nanotechnology Perceptions, 2644-2661.

[37] Sondinti, L. R. K., Kalisetty, S., Polineni, T. N. S., & abhireddy, N. (2023). Towards Quantum-Enhanced Cloud Platforms: Bridging Classical and Quantum Computing for Future Workloads. In Journal for ReAttach Therapy and Developmental Diversities. Green Publication. https://doi.org/10.53555/jrtdd.v6i10s(2).3347

[38] Danda, R. R. (2024). The Role of Machine Learning Algorithms in Enhancing Wellness Programs and Reducing Healthcare Costs. Utilitas Mathematica, 121, 352-364.

[39] Bauskar, S. R., Madhavaram, C. R., Galla, E. P., Sunkara, J. R., Gollangi, H. K. and Rajaram, S. K. (2024) Predictive Analytics for Project Risk Management Using Machine Learning. Journal of Data Analysis and Information Processing, 12, 566-580. doi: 10.4236/jdaip.2024.124030.

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

[41] Reddy, R. (2023). Predictive Health Insights: Ai And Ml's Frontier In Disease Prevention And Patient Management. Available at SSRN 5038240.

[42] Korada, L. (2024). Use Confidential Computing to Secure Your Critical Services in Cloud. Machine Intelligence Research, 18(2), 290-307.

[43] Sunkara, J. R., Bauskar, S. R., Madhavaram, C. R., Galla, E. P., & Gollangi, H. K. (2023). Optimizing Cloud Computing Performance with Advanced DBMS Techniques: A Comparative Study. In Journal for ReAttach Therapy and Developmental Diversities. Green Publication. https://doi.org/10.53555/jrtdd.v6i10s(2).3206

[44] 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.

[45] Eswar Prasad G, Hemanth Kumar G, Venkata Nagesh B, Manikanth S, Kiran P, et al. (2023) Enhancing Performance of Financial Fraud Detection Through Machine Learning Model. J Contemp Edu Theo Artific Intel: JCETAI-101.

[46] Laxminarayana Korada, V. K. S., & Somepalli, S. Finding the Right Data Analytics Platform for Your Enterprise.

[47] Polineni, T. N. S., abhireddy, N., & Yasmeen, Z. (2023). AI-Powered Predictive Systems for Managing Epidemic Spread in High-Density Populations. In Journal for ReAttach Therapy and Developmental Diversities. Green Publication. https://doi.org/10.53555/jrtdd.v6i10s(2).3374

[48] Sondinti, L. R. K., & Yasmeen, Z. (2022). Analyzing Behavioral Trends in Credit Card Fraud Patterns: Leveraging Federated Learning and Privacy-Preserving Artificial Intelligence Frameworks.

[49] Siddharth K, Gagan Kumar P, Chandrababu K, Janardhana Rao S, Sanjay Ramdas B, et al. (2023) A Comparative Analysis of Network Intrusion Detection Using Different Machine Learning Techniques. J Contemp Edu Theo Artific Intel: JCETAI-102.

[50] Korada, L. (2024). GitHub Copilot: The Disrupting AI Companion Transforming the Developer Role and Application Lifecycle Management. Journal of Artificial Intelligence & Cloud Computing. SRC/JAICC-365. DOI: doi. org/10.47363/JAICC/2024 (3), 348, 2-4.

[51] Subhash Polineni, T. N., Pandugula, C., & Azith Teja Ganti, V. K. (2022). AI-Driven Automation in Monitoring Post-Operative Complications Across Health Systems. Global Journal of Medical Case Reports, 2(1), 1225. Retrieved from https://www.scipublications.com/journal/index.php/gjmcr/article/view/1225

[52] Danda, R. R. Digital Transformation In Agriculture: The Role Of Precision Farming Technologies.

[53] Janardhana Rao Sunkara, Sanjay Ramdas Bauskar, Chandrakanth Rao Madhavaram, Eswar Prasad Galla, Hemanth Kumar Gollangi, et al. (2023) An Evaluation of Medical Image Analysis Using Image Segmentation and Deep Learning Techniques. Journal of Artificial Intelligence & Cloud Computing. SRC/JAICC-407.DOI: doi.org/10.47363/JAICC/2023(2)388

[54] Korada, L. (2024). Data Poisoning- What Is It and How It Is Being Addressed by the Leading Gen AI Providers. European Journal of Advances in Engineering and Technology, 11(5), 105-109.

[55] Kothapalli Sondinti, L. R., & Yasmeen, Z. (2022). Analyzing Behavioral Trends in Credit Card Fraud Patterns: Leveraging Federated

Learning and Privacy-Preserving Artificial Intelligence Frameworks. Universal Journal of Business and Management, 2(1), 1224. Retrieved from https://www.scipublications.com/journal/index.php/ujbm/article/view/1224

[56] Chitta, S., Yandrapalli, V. K., & Sharma, S. (2024, June). Deep Learning for Precision Agriculture: Evaluating CNNs and Vision Transformers in Rice Disease Classification. In 2024 OPJU International Technology Conference (OTCON) on Smart Computing for Innovation and Advancement in Industry 4.0 (pp. 1-6). IEEE.

[57] Gagan Kumar Patra, Chandrababu Kuraku, Siddharth Konkimalla, Venkata Nagesh Boddapati, Manikanth Sarisa, et al. (2023) Sentiment Analysis of Customer Product Review Based on Machine Learning Techniques in E-Commerce. Journal of Artificial Intelligence & Cloud Computing. SRC/JAICC-408.DOI: doi.org/10.47363/JAICC/2023(2)38

[58] Korada, L. Role of Generative AI in the Digital Twin Landscape and How It Accelerates Adoption. J Artif Intell Mach Learn & Data Sci 2024, 2(1), 902-906.

[59] Kothapalli Sondinti, L. R., & Syed, S. (2021). The Impact of Instant Credit Card Issuance and Personalized Financial Solutions on Enhancing Customer Experience in the Digital Banking Era. Universal Journal of Finance and Economics, 1(1), 1223. Retrieved from https://www.scipublications.com/journal/index.php/ujfe/article/view/1223

[60] Chitta, S., Yandrapalli, V. K., & Sharma, S. (2024, June). Advancing Histopathological Image Analysis: A Combined EfficientNetB7 and ViT-S16 Model for Precise Breast Cancer Detection. In 2024 OPJU International Technology Conference (OTCON) on Smart Computing for Innovation and Advancement in Industry 4.0 (pp. 1-6). IEEE.

[61] Nagesh Boddapati, V. (2023). AI-Powered Insights: Leveraging Machine Learning And Big Data For Advanced Genomic Research In Healthcare. In Educational Administration: Theory and Practice (pp. 2849–2857). Green Publication. https://doi.org/10.53555/kuey.v29i4.7531

[62] Pradhan, S., Nimavat, N., Mangrola, N., Singh, S., Lohani, P., Mandala, G., ... & Singh, S. K. (2024). Guarding Our Guardians: Navigating Adverse Reactions in Healthcare Workers Amid Personal Protective Equipment (PPE) Usage During COVID-19. Cureus, 16(4).

[63] Patra, G. K., Kuraku, C., Konkimalla, S., Boddapati, V. N., & Sarisa, M. (2023). Voice classification in AI: Harnessing machine learning for enhanced speech recognition. Global Research and Development Journals, 8(12), 19–26. https://doi.org/10.70179/grdjev09i110003

[64] Vankayalapati, R. K., Edward, A., & Yasmeen, Z. (2021). Composable Infrastructure: Towards Dynamic Resource Allocation in Multi-Cloud Environments. Universal Journal of Computer Sciences and Communications, 1(1), 1222. Retrieved from https://www.scipublications.com/journal/index.php/ujcsc/article/view/1222

[65] Mandala, V., & Mandala, M. S. (2022). ANATOMY OF BIG DATA LAKE HOUSES. NeuroQuantology, 20(9), 6413.