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# Machine Learning Architecture to Financial Service Organizations

**K. Palanivel[1*]**

Computer Centre, Pondicherry University, Puducherry, India

*Corresponding Author: kpalanivel.cce@pondiuni.edu.in, Tel.: +91-413-2654650

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***Abstract*—** Financial Services is a heavily regulated industry and organizational complexity that is driven by business segments, product lines, customer segments, a multitude of channels and transaction volumes. The role of data onto the financial services institutes has grown exponentially in recent years and is advancing rapidly. Traditional data solutions were built based on the demands of earlier days using technologies available at that point in time. However, the ever-growing amount of data and the insights that can now be extracted from it have rendered these solutions obsolete. A modern technology and advanced analytical solutions can only handle current demands and achieve business goals. Todays, Machine Learning (ML) gains traction in digital businesses and embraces it as a tool for creating operational efficiencies. The ML algorithm can analyze thousands of data sources simultaneously, something that human traders cannot possibly achieve. They help human traders squeeze a slim advantage over the market average. In addition, it has given the vast volumes of trading operations that small advantage often translate into significant profits. Robust architecture designs is one of the common traits of a successful enterprise financial ecosystem. This article discusses the use cases, benefits and pitfalls and the requirements of ML architecture to financial services institutes. This proposed ML architecture provides a fully functional technical picture for developing a cohesive business solution.

***Keywords*—**Advanced Analytics, Machine Learning, Machine Learning Model, Machine Learning Architecture, Financial Service Institutes, Digital Business.

## I. INTRODUCTION

The high-growth financial services organizations/ institutes (FSI) are vital to the modern economy. Financial services organizations such as banking, insurance, capital markets/ investment, retail and business will continue to focus on revenue growth and higher margins. These financial organizations are gravitating towards the expansion of wealth management portfolios to ensure lower risk and consistent fee-based revenue. The FSI shall be expected to lead digitization and automation initiatives. It is noted that the financial sector is lagging behind other sectors. For example, banking organizations develop new revenue streams by entering new markets and service areas.

FSI provides capital for companies to invest in their futures. They offer clients advice on investment vehicles and supports risk management of various life and corporate events through insurance. This multifaceted economic sector is core to keeping society functioning and progressing. It can collect and leverage data at an astonishing pace. With an abundance of choice among industry providers, individual and enterprise clients are now unforgiving towards mistakes, be it inaccurate information resulting in higher loan rates, tardy money movement causing lost investment opportunities. FSI must be at the forefront of the data and analytics game. They are ensuring data integrity, increasing processing speed and accuracy, and reaping the rewards of advanced analytics tools and techniques, including streamlined operations and superior products.

FSI has always been the first to adopt technological innovations for business process optimization and better customer interaction. As traditional revenue streams struggle to remain profitable, FSI are engaging in digital transformation. They are looking into offering novel, higher-margin products and services while seeking to improve operational efficiency. They are striving to provide business analysts with better self-service capabilities, and they are working on providing customers with real-time information, mainly in the service of up-selling, cross-selling, fraud detection, and risk management initiatives.

### *A. Challenges*

The financial data sets are only growing larger, and as the volumes increase, so does the challenge of detecting fraud. The FSI needs better technological solutions to detect and prevent fraud. In addition, traditional Data Warehousing and

 

Data Marts can be inflexible. A key challenge with legacy data warehousing technologies is the cost of maintaining and accessing data efficiently. Moreover, these systems are not designed to process unstructured data or support the blending of data from multiple structured and unstructured sources while adhering to data governance and data lineage policies. Some of the challenges of today's FSI are accurate data analysis, frees up fraud analysts, reduction of false positives, effective attack detection and achieve regulatory compliance.

*B. Technological Solutions*

Technologies such as Robotic Process Automation (RPA), Cognitive Automation, Natural Language Processing (NLP), Artificial Intelligence (AI), Machine Learning (ML) and Deep Learning (DL) are transforming how FSI operate [20]. They are becoming aware of the potential of AI and ML technologies. They explore how advanced analytics could enable them to streamline operations, improve product offerings and enhance customer experiences.

- AI is taking the FSI by storm. It helps FSI save time and money with algorithms to generate insights, improve customer service. They make predictions about company sales performance and churn. For example, in the banking sector, AI enhances efficiency, offers data insights, and manages risk.
- Deep Learning (DL) is a subset of ML. It is especially useful for analyzing complex, rich, and multidimensional data such as speech, images, and video. It works best when used to analyze large data sets.
- NLP allows users to extract or generate meaning and intent from the text in a readable, stylistically natural, and grammatically correct form. NLP powers the voice and text-based interface for virtual assistants and chatbots. NLP is increasingly being used to query data sets as well.
- With ML technologies, computers can be taught to analyze data, identify hidden patterns, make classifications, and predict future outcomes. ML typically requires technical experts who can prepare data sets, select the right algorithms, and interpret the output.

Developing strong AI and ML solutions can affect the cost and revenue structures of financial organizations and it can improve the customer experience [11]. FSI realize they have a head start with the application of Advanced Analytics since they have large data sets and experience with analytical tools.

ML surmounts the challenges discussed in the previous section and can drive business growth by producing fresh insights previously buried in mountains of Big Data. Through model training, the value of a ML solution can continue to grow as it consumes new data and further improves accuracy, reaching levels that far surpass traditional systems. It is making ML a good investment for virtually any enterprise.

Advanced Analytics and ML are intertwined in several ways. Both use computer programming along with various statistical and Data Mining techniques including time series analysis, text analysis, random forest, decision trees, pattern matching, forecasting, visualization, semantic and sentiment analysis, network and cluster analysis, to name a few. They aim at analysing data to discover patterns and draw insights.

*C. Machine Learning Technology*

ML is a technique for analysing data. It is a system fuelled by data with the ability to learn and improve by using algorithms that provide new insights without being explicitly programmed to do so. ML is best suited for dealing with Big Data. Organizations overwhelmed with data are using multiple ML frameworks to increase operational efficiencies and achieve greater business agility.

The finance industries that have become data-driven and can, therefore, benefit from ML are banking and insurance companies, healthcare and life sciences, customer relationship management (CRM) and consumer behaviour, failure prediction for preventive maintenance, smart machines, workforce management and IT operations. For example, banking and insurance companies use ML to reduce fraud. Businesses in every industry can gain a competitive advantage and generate new revenue by delivering products and services that are more personalized, efficient, and adaptive. The FSI are undergoing digitalization at a dizzying rate, and this has resulted in a massive increase for data.

Rapid increases in processing power and storage, combined with advances in ML and other analytics techniques, now offer FSI a high-value opportunity to leverage their growing wealth of business data to improve customer service, boost operational efficiency, and reduce risk. ML offers the important benefits that can lead to competitive advantage of velocity of insight, the volume of processed data, operational efficiency, and the intelligence to learn autonomously.

*D. Data Science in Finance Services*

Finance services has been utilizing data over the years. Data Science analysis in finance services ensures the decisions made are as certain as possible. When dealing with finance services, numerous choices are made in a brief period. These choices can be, transient choices to real choices having long haul consequences that could represent a critical risk to a firm or corporation. There are high stakes associated with these choices. Making them for sound information and logical standards would give everyone significant serenity and would moderate the risks in question. Figure 1 shows the interconnection among technology, Data Science and business.

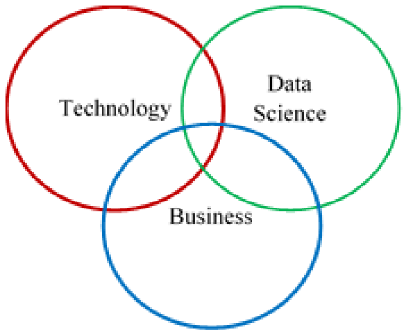


Figure 1. Interconnection among Technology, Data Science and Business

The Data Science can be applied in finance [1] in the areas such as algorithmic trading, consumer analytics, customer data management, financial risk management, fraud detection, providing personalization and real-time data analytics.

- *Algorithmic Trading in Finance.* It is a main aspect of FSI. Advanced mathematical equations and high-speed calculations assist FSI in designing fresh commercial approaches for algorithm trading. There are huge information pools and information current in algorithmic trading. They include a model that measures and explains the fundamental stream of information. The Algorithmic Trading analysis engine is designed to create better knowledge of huge datasets by forecasting the market.
- *Consumer Analytics.* The core business of FSI is customer customization. Data scientists and analysts can obtain information on customer habits and can make proper company choices with the assistance of actual-time analysis. FSI like insurance firms utilize consumer analysis to assess client life, boost sales and decrease costs by less than zero clients.
- *Customer Data Management.* Customer data is necessary for financial organizations. Social media and a big amount of operations contribute to the quantity and range of information. This data is in two types, which are organized (or structured) data and unorganized (or unstructured) data. While organized information is simpler to use, unorganized information creates many challenges.
- *Financial Risk Management*. Financial lending is a job that poses potential risks for a financial institution. Risk analytics is an interdisciplinary discipline where understanding mathematics, statistics, and solving problems are crucial. Because risk analysis controls and reduces the likelihood of losses and the severity of the damage, information is central to it. Identifying, tracking and setting priorities for the risks are key steps towards risk management.
- *Fraud Detection.* For financial firms, fraud is an important issue. With an increasing amount of transactions, the risks of fraud have risen. Credit card fraud is among the most common fraud practices in financial firms. These fraud detection alert organizations to aberrations in financial transactions, urging them to close the account to mitigate losses.
- *Providing Personalized Services.* FSI offers customized solutions to their clients. They use a range of methods to analyze and create insight into client data. Besides, they rely on voice recognition and natural linguistic analysis to give their clients improved interactivity. The information supplied by customers enables FSI to gain an accurate understanding of their client requirements, which would boost profitability. This assists the FSI in optimizing their policies and providing their clients with better services.
- *Real-Time Analytics.* Data analysis is always in the manner of batches in standard analytics. This led to difficulties for different fields that needed real-time data to offer insight into current circumstances. Technological developments, as well as the growth of dynamic data pipelines, permits only for a limited lag in access to the data. With that kind of implementation in finance of Data Science, organizations are in a position, without lag, to monitor operations, loan values, and other economic characteristics.

Data Science provides corporations with massive opportunities to enhance client commitment, safeguard their earnings by managing risks, and remain ahead in the fast growing, ever changing financial as well as the artificial intelligence world [1]. Many resources available in AI such as NLP, Data Mining and Text Analysis produce valuable insights from the data in FSI use machinery to create insights into the clients and to obtain Business Intelligence (BI).

### *E. Artificial Intelligence in Financial Services*

AI and ML are driving transformation across virtually all industries and disciplines. They seem to be connected sometimes but they are quite distinct in the area of computing. They are helping businesses streamline internal processes to improve efficiencies, make sense of vast amounts of data to drive intelligent decision making, and create new, innovative services to improve the customer experience. The FSI stands to gain incredible value from AI, leading many financial organizations to eagerly work to leverage the technology to more effectively service their customers, manage new and ongoing investments, combat fraud and augment their workforce. AI technology must include the following fundamental capabilities [2]:

1. *Ability to personalize.* AI systems recognize the unique, individual behaviour of an entity over time. This is a crucial capability for FSI looking to successfully protect and serve their customers, employees and any other audiences.
2. *Ability to adapt to new information*. AI technology is data agnostic, works with any data, any format, from any sources and produces results in real-time.

 

3. *Ability to self-learn*. AI systems can learn from every activity associated with each specific entity, as well as the behaviours associated with entities over time.

AI can focus on individual entities, such as consumers and devices and their unique attributes and behaviours, which enables FSI to offer hyper-personalized financial and payments services. AI systems can perform this type of analysis at scale and concerning privacy, allowing flexibility to be configured to fit into the model governance framework of financial organizations. AI in FSI need to prioritize the technology's ability to learn and make real-time observations from interactions with human users. Using this knowledge, AI can then create virtual representations of every entity with which they interact, building a digital profile that optimizes customer-facing payments and banking services.

Additionally, AI systems can provide FSI with the ability to collect information on any number of actors in an ecosystem. This information can then be leveraged to further teach the AI system how to best manage different operations and successfully personalize on a massive scale. Decision-making is therefore specific to each cardholder, bank or terminal and no longer relies on logic that is universally applied to all cardholders, regardless of their characteristics. Banks, credit card issuers, and other financial organizations are increasingly relying on AI technology [19] to screen potential customers, intelligently investing, and provide better customer services. Many companies have already started implementing intelligent solutions such as advanced analytics, process automation, Robo-advisors, and self-learning programs. However, a lot more is yet to come as technologies evolve, democratize, and are put to innovative uses. To effectively capitalize on the advantages offered by AI, FSI may need to fundamentally reconsider how humans and machines interact within their organizations as well as externally with their value chain partners and customers. Rather than taking a siloed approach and having to reinvent the wheel with each new initiative, FSI executives should consider deploying AI tools [20] systematically across their organizations, encompassing every business process and function.

To realize the full potential of AI and make the most of such a substantial technological investment, FSI must recognize the stark differences between various supervised and unsupervised learning technologies and carefully consider which functions are best suited to specific business objectives. In doing so, FSI of all sizes can tap into the tremendous growth and development opportunities AI systems are capable of providing.

### F. *Machine Learning in Financial Services*

ML is a field of study that applies the principles of computer science and statistics to create statistical models, which are used for future predictions *based on past data or Big Data* and identifying patterns in data. ML is a technology that helps to improve the services provided by systems, Web, and smartphones. *Machine Learning can be formally defined as a data analysis technology for knowledge to be extracted by the system without any explicit definition to conduct the same based on a series of observations* [13, 18].

ML allows software applications to take an algorithmic approach to parse, analysing and inferring insights from data to support assisted or automated identification and decision-making. ML is a type of data analysis technology that extracts knowledge without being explicitly programmed to do so. Data from a variety of potential sources is fed to the ML system, which uses that data, fit to algorithms, to build its logic and to solve a problem or derive some insight. ML is itself a type of AI that allows software applications to become more accurate in predicting outcomes without being explicitly programmed. ML can be split into three major sub-disciplines: supervised learning, unsupervised learning and reinforcement learning.

- *Supervised learning,* where observations contain input/output pairs (data). These sample pairs are used to *train* the ML system to recognize certain rules for correlating inputs to outputs. E.g., types of ML that are trained to recognize a shape based on a series of shapes in pictures.
- *Unsupervised learning,* where those labels are omitted. In this ML, rather than being "trained" with sample data, the ML system finds structures and patterns in the data on its own. E.g., types of ML that recognize patterns in attributes from input data that can be used to make a prediction or classify an object.
- *Reinforcement learning,* where evaluations are given about how good or bad a certain situation is, E.g., types of ML that enable computers to learn to play games or drive vehicles.

The basic objective of ML is to build algorithms that can receive input data and use statistics for prediction of an output value within an acceptable range. It provides the ability to automatically obtain deep insights, recognize unknown patterns, and create high performing predictive models from data, all without requiring explicit programming. The basic concept of ML is relatively simple as shown in Figure 2. The basics of ML involve input data, the learning process itself and output data.

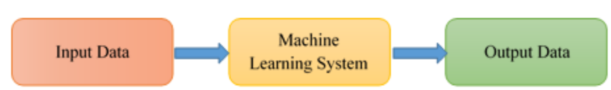


Figure 2. The basic concept of Machine Learning System

*Input data.* A wide variety of data come from a variety of sources, such as enterprise systems (ERP), social network, mainframe databases, and Internet of Things (IoT) devices can be used as input for ML purposes. They may be structured or unstructured in nature. The volume of data is very large. They may be static or motion. More data often yields more insights. This is exacerbated by the digital business era, in which sources and volumes of information are exploding.

*Learning.* The ML used for business purposes is either supervised or unsupervised in nature. There are many different types of algorithms and ML routines, which can be used to accomplish different goals. Additionally, there are often different learning methods, such as eager and lazy. *Eager learning methods* evaluate training data and eagerly begin computing before receiving new data. They generally depend more on the upfront evaluation of training data to compute without the need for new data. As a result, eager learning methods tend to spend more time processing the training data. *Lazy learning methods* delay processing and data evaluation until new test data is provided. As a result, lazy learning methods are often case-based, spending less time on the training data and more time on predicting. These methods govern how to process training data and that governance will determine to compute and storage requirements.

*Output Data.* ML can be used to deliver results that are either predictive or prescriptive. The results can deliver outputs that classify information or highlight areas for exploration. This output data may be stored for analysis, delivered as reports or fed as input into other enterprise applications or systems.

It is worth pointing out that DL is a subset of ML, and ML is, in turn, a subset of broader AI. ML is applied in FSI as process automation, detecting frauds, identifies suspicious account behaviour, financial monitoring, enhance network security, and cybersecurity networks. ML algorithms fit perfectly with the underwriting tasks that are so common in finance and insurance. In the FSI, ML algorithms can predict market risk, reduce fraud, and identify future opportunities. Table 1 provides the common types of ML used in business, and it lists examples of the types of business applications they can be used to solve.

Table 1. Types of Machine Learning Algorithms and Problem

| S/L | ML Type | ML Model/ Algorithm /Task | ML usage/ Examples in Business |
|---|---|---|---|
| 1 | Supervised | Neural Network | Predicting financial Results, Fraud detection |
| 2 | Supervised | Classification Regression | Spam filtering, Fraud detection |
| 3 | Supervised | Decision Tree | Risk assessment, Threat management systems, Any optimization problem |
| 4 | Unsupervised | Cluster Analysis | Financial transactions, Streaming analytics in IoT, Underwriting in insurance |
| 5 | Unsupervised | Pattern Recognition | Spam detection, Biometrics, Identity management |
| 6 | Unsupervised | Association Rule Learning | Security and intrusion detection, Bioinformatics, Manufacturing and assembly |

ML technology can reduce financial risks in several ways [3]:

a. ML algorithms can continuously analyse huge amounts of data (for example, on loan repayments, car accidents, or company stocks) and predict trends that can affect lending and insurance companies.
b. ML can also be applied to early warning systems. ML enhanced early warning systems can be used by banks and other FSI to predict anomalies, reduce risk cases, monitor portfolios, and provide recommendations on what to do in cases of fraud.

Many FSI today have moved from using traditional predictive analysis to using ML algorithms to forecast financial trends. With the help of ML, financial specialists can identify market changes much earlier than with traditional methods.

### *G. Use Cases of ML in Financial Services*

The era of localized banking with manual paper transactions would remind the earlier generation about the time and physical pain of record keeping meted out from the banking system. The long queues, the token systems, necessity of physical presence etc. even for transactions such as depositing or withdrawing a few currency notes must have taken a toll on health and career, leave alone the pain of ones who ran pillar to post for loans.

Over the years, the customers are slowly phased into a digital or dynamic banking system where they could withdraw money from ATMs and then came the Internet banking and Mobile banking. The banking revolution has changed the localized branch-based system to networks and digital landscape creating utmost convenience to the end-users. The ML is rapidly expanding. The FSI is reaping maximum benefits. Some ML use cases [23] in finance are fraud detection, assessing the applicant's creditworthiness, enhanced customer support, predicting customer behaviour, etc.

 

*Fraud Detection and Prevention***.** With more technological innovations, there are more risks of fraudulent transactions for FSI. The FSI is suffering from fraud-related losses more than any other industry. The financial sectors where ML is used for fraud detection are insurance and banking.

i. In the insurance sector, the ML system can detect unusual behaviour, or anomalies, and flag them. ML algorithms not only give detailed information on suspicious behaviour but also even suggest measures that can be taken to resolve situations and protect programs. In the banking sector, electronic payments are extremely vulnerable to fraud.
ii. In banking, ML can delay potentially fraudulent transactions until a human makes a decision. Unlike humans, machines can weigh the details of a transaction and analyze huge amounts of data in seconds to identify unusual behaviour. ML technologies are also used by banks for biometric-based user authentication to ensure the security of financial operations.

*Better Customer Support***.** With the help of modern technologies, banks and other financial institutions can make their services digital. The ML can be applied to customer support using chatbots, personalized experience and sentiment analysis.

i. Using *chatbots*, ML helps financial institutions to solve customer issues immediately. They provide customers with instant information about balances, transactions, and other related matters. Chatbots are beneficial in banking because they save money, increase customer engagement, and streamline customer support.
ii. *Personalization* is the key to building customer loyalty and trust in any business or organization. In finance service, ML algorithms can analyze customers' data and predict what services they might like or give helpful advice. For example, Capital One. This program can detect if a customer has been charged twice for the same product or service and notify them about it.
iii. *Sentiment Analysis* is a process of analyzing customers' emotions, opinions, and attitudes toward other individuals, products, or services. In the financial industry, institutions use ML algorithms to analyze financial news from different sources and make predictions of possible stock market trends. The sentiment analysis lies in the ability to process huge amounts of data from different news channels in seconds.

*Prediction of Stock Market Changes.* ML technology analyzes past and real-time data about companies and predicts the future value of stocks based on this information. Besides, ML algorithms can even hunt for news from different sources to collect any data relevant to stock predictions. For example, Chatbots and Robo-advisors are growing trends in the finance industry. In future, there will be facial and voice recognition or other methods of biometric authentication for security.

*Anti-Money Laundering (AML).* The money laundering is the major issue for financial services that is apart from cost, significant legal and reputational risks. In the rapid development of business process automation in FSI as a part of cost cutting, it cannot avoid Money Laundering [24]. To approach AML, it needs to incorporate the advance and rapidly developing technologies of Regulation Technology (or RegTech). Process automation can deliver efficiencies in high volume transactions through software-based rules, alerts and AML case management. RegTech can be automated in compliance data management, employee surveillance, fraud prevention and audit trail capabilities. It is anticipated that RegTech would be powerful to mitigate money-laundering activity efficiently and cost-effectively, shortly. Even greater improvements in the field of RegTech are entirely within our reach.

Applying ML for any practical use case requires beside a good knowledge of ML principles and technology also a strong and deep knowledge of business and IT architecture and design aspects.

### *H. Advantage of ML in Finance Services*

Banks. Insurance and Capital Markets organizations require extreme performance as they start leveraging real-time analytics and ML for many strategic initiatives such as risk management, fraud detection, compliance, and consumer metrics. Analyses time-sensitive data now, enriched with historical data, help address the above initiatives while driving business impact through efficient operations and enhanced customer experience.

- *It decreases the risk of trade reconciliation.* The FSI can reduce risk exposure and meet regulatory requirements while lowering operational costs.
- *Real-time risk data store and operational intelligence.* Real-time analytics (RTA) and AI with transactional processing help firms evaluate the risk in their portfolio. Leveraging the combination of analysis and simulations running directly against transactional data, and ML, financial services firms can run intra-day risk analysis and power their insight-driven transformation.
- *Detect fraud and prevent money laundering.* Deploying and running RTA and ML on data as it is born can help financial organizations detect and prevent money laundering and other fraudulent activities while eliminating the need to provision new data stores for fraud detection workflows. FSI can reduce risk exposure and meet regulatory requirements while lowering operational costs.
- *Enhance Customer Experience.* FSI can differentiate in a highly competitive market by knowing and understanding the customers' sentiments, intentions and past activities

 

are facilitated by ingesting real-time customer interaction data at high throughput and analyzing the data now as it is born. Enriching these insights with historical data, combined with sub-second response times, powers personalized customer services including opening new accounts, loan requests or instant payment execution – making their customers happy.

In addition, DL and predictive analytics help identify chances of churn and manage up. Analytical solutions have grown multifold over the last decade, in terms of both their sophistication and the resulting business impact they create. There is a range of analytics solutions that FSI are deploying today. For financial institutes, advanced predictive and prescriptive analytics are now starting to generate powerful insights.

By capturing and leveraging massive volumes of data, FSI can capitalize on new data-driven business opportunities [16]. The goal is to create a solid data management foundation that supports the analysis of both enterprise data and Big Data. Once this foundation is established, it can begin implementing ML algorithms to support automated decision-making and data-driven process, optimization helping to generate insights that create better customer experiences, improve operational efficiency, and drive sales.

*I. Today's Business Trends*

Business use of ML is gaining momentum due to the increasing pervasiveness of the technology and the rising discovery of business benefits. The data-rich nature underpins a digital business. The huge masses of data that are now being collected from ERP, Social Medias, IoT sensors and other new information sources are overwhelming the abilities of businesses to interpret them and derive value and insights from them. Because ML can relatively quickly and efficiently sift through and interpret these mountains of data, many businesses are seizing the opportunity to uncover latent insights that could deliver a competitive edge.

ML is particularly well suited to gaining a competitive edge in digital business because it offers speed, power, efficiency and intelligence. The benefits that ML can provide will likely drive interest from business leaders. If the IT organization is proactive about planning and is preparing the IT environment for ML now, it will be better positioned to deliver benefits. To be ready, technical professionals should start by planning in areas related to the ML process**,** ML technical architecture and required skills.

The paper is organized as follows: The *introduction* section provides necessary information on various technologies in FSI such as AI in Financial Services, ML in Financial Services, etc. The *related work* section review the literature in the areas of ML model and ML architectures to FSI. The *Results & Discussion* section presents the requirement, challenges, technologies applied, financial analytic model and analytic architecture required to design ML architecture to FSI. The *evaluation* section provides a detailed evaluation of the proposed ML architecture. Finally, the results are summarized in *the conclusion* section.

## II. RELATED WORK

The objective of this article is to design an ML architecture to FSI. For any ML architecture, financial applications data is of utmost importance. Financial Applications data is transformed into meaningful and usable information. Information that can be used for humans or information that can be used for autonomous systems to act upon. Financial Applications data can be used to train the ML model originating from the business processes. It needs to use data from other sources. E.g., photo collections, traffic data, weather data, financial data, etc. The above data are 'Big Data' in nature. Big data [28] is data where the volume, velocity or variety of data is too great. It refers to technologies and initiatives that involve data that is too diverse, fast changing or massive for conventional technologies, skills and infrastructures to address efficiently.

*A. Machine Learning Data*

Every ML problem starts with huge volume of data. For any project, most of the time large quantities of training data are required. ML incorporates all kind of data, e.g. structured, unstructured, metadata and semi-structured data from email, social media, text streams, images, and machine sensors. One of the challenges with ML is to automate knowledge to make predictions based on information or data. ML requires the right set of data that can be applied to a learning process. A financial organization with big data can help improve the accuracy of ML models. With Big Data, it is now possible to virtualize data so it can be stored most efficiently and cost-effectively whether on-premises or in the cloud. Besides, Data Mining [ ] is used to explain and understand the data. One of the challenges with ML is to automate knowledge to make predictions based on information or data. With more data, it can train models that are more powerful.

The ML practitioners often engage with images, text, audio, video, structured data, product reviews (Amazon, Yelp and App Stores), user-generated content (Tweets, Facebook posts, StackOverflow questions), troubleshooting data from the ticketing system (customer requests, support tickets, chat logs). Hence, when developing the ML architecture be aware that data is most of the time.

*B. Machine Learning Life Cycle*

To build custom ML algorithms and applications, FSI must develop a life cycle for ML to support the highly iterative building, testing and deployment of ML models. The process for planning, creating, testing and deploying ML systems is similar to any other application development life cycle. However, a slightly adapted life cycle is needed to focus more on ML model evaluation and tuning. Figure 3 describes the adapted ML model development life cycle. The adopted process will guide technical professionals in implementing a continuous model deployment and control framework for automating the process of developing, testing, deploying and monitoring ML models. The adapted life cycle offers the same tasks as traditional data and analytic services, with the addition of subtasks that enable ML capabilities. A description of the updated processes of Figure 3 is described in understanding the basic architecture needed for ML solutions.

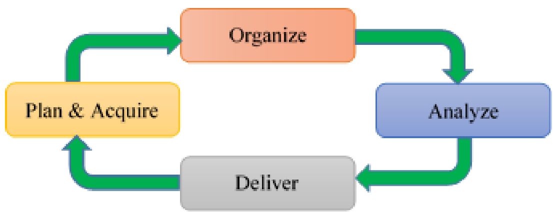


Figure 3. The adapted ML development life cycle model

The development life cycles must support *collaboration* for heterogeneous teams and technologies, *monitoring* of ML models with statistical analysis capabilities, *reusability* of ML models for rapid development and *interoperability* between different analytic platforms and ML frameworks.

*C. The Machine Learning Process*

Figure 4 derived from Figure 2 shows the basics of ML include data ingestion (structured and unstructured), data analysis and model training, and results in a generation. The self-learning capabilities continuously improve the model's accuracy.

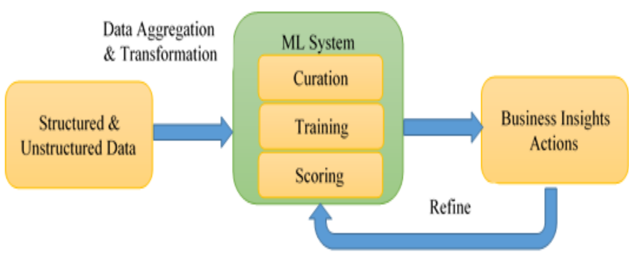


Figure 4. The basics of Machine Learning Process.

To set up ML architecture for any applications it requires good insight into the various processes that play a crucial role. Therefore, to develop a ML good architecture it should have a solid insight in business process, end-user interaction, development and maintenance process and the critical quality aspects of security, privacy and safety aspects. In its core an ML process, exist of many typical steps exists in an ML process are:

i. Determine the problem the end-users want to solve using ML technology
ii. Search and collect training data for the ML development process.
iii. Select an ML model
iv. Train the ML model with the collected data
v. Test the ML system using test data
vi. Validate and improve the ML model with feedback.
vii. Improve the model with more training data or by making model adjustments.

*D. Machine Learning Frameworks*

ML frameworks offer software building blocks for designing, training and validating the ML model. The ML framework is using a high-level programming interface. It mostly depends on the complexity and novelty of the solution that the designer intends to develop.

To create ML architecture within the specific context, choosing an ML framework that suits the specific use case is a severely difficult task. The factors that must be considered to choose an ML framework are stability, performance, features, flexibility, transparency, and license. There are multiple factors to consider while choosing the ML framework like community support, performance, third-party integrations, use-case, and so on. However, one important thing to keep in mind while selecting the library/framework is *the level of abstraction you want to deal with*.

There are many open-source ML frameworks available with the above features, which enable us to create ML applications. The most popular open-source implementation of MapReduce is *Apache Hadoop, Apache Spark and Apache Mahout*. All the mature Deep Learning frameworks like TensorFlow, MxNet, and PyTorch also provide APIs to perform distributed computations by model and data parallelism. In addition, there are frameworks at higher-level like *hooved and Elephas* built on top of these frameworks. Therefore, it all boils down to what the use-case is and what level of abstraction is appropriate for the designer.

In addition, a distributed ML framework [13] shall take care of data handling, task distribution, and providing desirable features like fault tolerance, recovery, etc.

*E. Machine Learning Model*

ML models are the work products produced by working with the ML frameworks. By the definition, a ML model is "*a mathematical configuration obtained after applying specific machine learning methodologies*" [13]. Using the extensive range of application programming interfaces (APIs), building an ML model is straightforward nowadays. Based on the type of tasks, it can be classified as classification, clustering, deep learning, dimensionality reduction and regression, and they have shown in Table 2.

Table 2. Types of Machine Learning Model

| S/N | Type | Definition/Features | Example |
|---|---|---|---|
| 1 | Classification | Predicts the type or class of an object within a finite number of options.<br>The output variable is always categorical. | K-Nearest Neighbors, Naive Bayes,<br>Logistic Regression, SVM,<br>Decision Tree |
| 2 | Clustering | Grouping similar objects together.<br><br>Help to identify similar objects automatically without manual intervention. | K Means,<br>K Means++,<br>K medoids,<br>Agglomerative clustering,<br>DBSCAN |
| 3 | Deep Learning | Deals with neural networks.<br><br>Based on the ANNs | Multi-Layer perceptron,<br>Convolution Neural Networks,<br>Recurrent Neural Networks,<br>Boltzmann machine,<br>Autoencoders, etc. |
| 4 | Dimensionality Reduction | Used to predict the independent variable (or) the real-world datasets the number of variables is too high.<br><br>Bring the curse of overfitting to the models. | PCA,<br>TSNE,<br>Singular Value Decomposition |
| 5 | Regression | It is a set of problems where the output variable can take continuous values. | Linear Regression,<br>Lasso Regression,<br>Ridge Regression,<br>SVM regression,<br>Decision Tree Regression, etc. |

The ML algorithm finds patterns in the training data such that the input parameters correspond to the target. The output of the training process is an ML model that can use to make predictions. There are broadly three types of ML algorithms. They are supersized (e.g. regression, decision tree, random forest, KNN, logistic regression, etc.), unsupervised (e.g., Apriori and K-means) and reinforcement (e.g. Markov decision process) learnings. The list of commonly used machine learning algorithms is linear regression, logistic regression, decision tree, support vector machine (SVM), Naive Bayes, k-Nearest Neighbors (kNN), K-Means, Random Forest, Dimensionality Reduction Algorithms, Gradient Boosting algorithms (GBM, XGBoost, LightGBM and CatBoost), etc. It can use every programming language for developing the ML application. The suitable languages for applying ML are Python, Java and R.

Choosing a proper ML model for a particular use case is very important to obtain the proper result of an ML task.

*F. Machine Learning Platform*

An ML model is the output generated once it trains the ML algorithmic program with data. After training, once it gives a model with associated input, the output is provided. An ML platform for automating and quicken the delivery lifecycle of prophetic applications capable of huge data processing adopting machine learning or connected procedures. ML is growing rapidly. It is very important to choose the proper ML platform that leads to the success of building ML models using end-to-end approaches. The list of ML platforms are Microsoft Azure, IBM Watson, Amazon, AI-One, Apache PredictionIO and H2O. Table 3 shows different types of ML platforms.

Table 3. Different Types of Machine Learning Platforms

| S.N | ML Platform | Functions | Examples |
|---|---|---|---|
| 1 | AI-One | • Developed for the developers. | The tools support ML and AI structures. |
| 2 | Amazon Machine Learning platform | • Offers ready-made and simply available prediction models for the developer.<br>• Uses a pay-as-you-go model. | AI toolkits provided by AWS, which also include Amazon Lex and Amazon Polly. |
| 3 | Apache PredictionIO | • Open-source stack | Apache PredictionIO |
| 4 | H2O | • Conjointly offers the tools needed to analyze data sets.<br>• Designed for Python, R & Java by H2O.ai.<br>• Open Source and commercial | Free Open Source ML - H2O, Sparkling Water & H2O4GPU<br>Commercial product - H2O Driverless AI. |
| 5 | IBM Watson platform | • Developed for both developers and users.<br>• Provides system programs and queries, prediction and assembles tools.<br>• Allows powerful information visualizations. | - |
| 6 | Microsoft Azure | • Permits developers to build the models.<br>• Provides SDKs and services to quickly prep information, train, and deploy ML models. | PyTorch, Tensor Flow, scikit-learn, etc. |

The Table 3 gives the best platforms the user can use. It can be either cloud-based or production-based platforms.

To design the ML architecture, it must consider each step of the ML process as discussed in the ML process. The resulting architecture must be flexible enough to adapt to new sources of data, elastic enough to handle varying workloads, and powerful enough to crunch through terabytes of data. It also needs to consider overarching architecture components that provide security and governance, as well as create a solution that supports Agile and DevOps methodologies.

ML tools are AI algorithmic applications that provide systems with the ability to understand and improve without considerable human input. It enables software, without being explicitly programmed, to predict results more accurately. ML tools with training wheels are supervised algorithms. They require an individual to schedule both the input and the desired output and provide feedback on the accuracy of the results. ML tools are consists of preparation and data collection, building models, application deployment and training.

### *G. Machine Learning Architecture*

ML Architecture as a subject has evolved in the recent periods from a concept of fantasy to proof of reality. The basic idea is to determine if the machines are capable of learning from the data provided to them and become able to produce repeatable actions with higher reliability and efficient decision-making. ML Architecture can be categorized based on the algorithm used in training. They are supervised learning, unsupervised learning and reinforcement learning [13]. Figure 5 shows the decision flow architecture of the ML system.

The decision flow architecture of ML has different major components and they are *data acquisition, data processing/integration, feature analysis, data modelling, execution and deployment.* These components explained in more detail below:

*Data Acquisition.* In this component, large volume of data is collected from a variety of sources and prepared for ingestion for ML data processing platform. The collection of high volumes of data may be from a variety of potential sources, such as ERP databases, mainframes or instrumented devices that are part of an IoT system. This portion of the architecture contains the elements needed to ensure that the ingestion of ML data is reliable, fast and elastic. This data is handled before ingestion depends on whether data is coming in discrete chunks or a continuous flow. Discrete data may be stored and forwarded via a batch data warehouse. If streaming data is used, a stream processing platform may be needed here. This stream-processing capability may be needed to screen out data not needed for processing, to store some in the data warehouse for future reporting, or to pass a portion along if it is needed for immediate processing.

*Data Processing (or Data Integration).* The data processing component is where ingested data is forwarded for the advance integration and processing steps needed to prepare the data for ML execution. This may include modules to perform any upfront data transformation, normalization, cleaning and encoding steps that are necessary.

*Feature Analysis.* Much of the data ingested for processing may include features or variables that are redundant or irrelevant. The feature analysis enable the ability to select and analyze a subset of the data to reduce training time, or to simplify the model. In many cases, feature analysis is a part of sample selection. This component filter data that may violate privacy conditions or promote unethical predictions. To combat privacy and ethical concerns, users should focus on removing features from being used in the model.

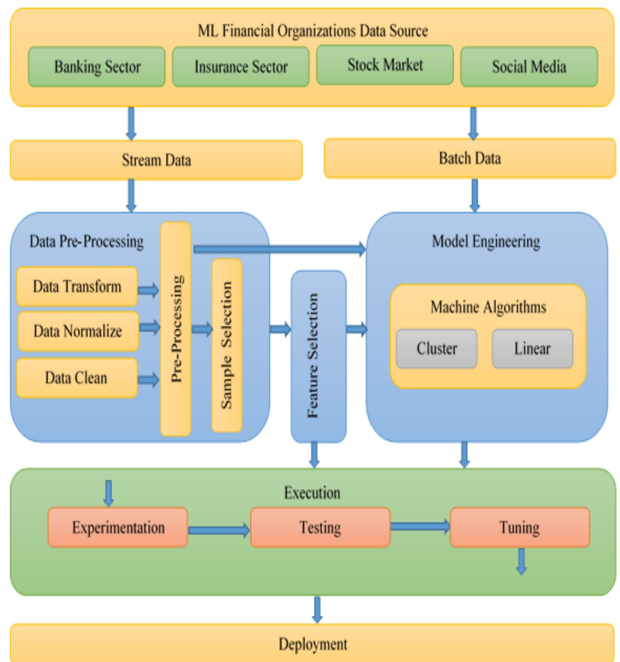


Figure 5. Architecture of ML system.

*Data Modelling.* The data modelling component is where algorithms are selected and adapted to address the problem that will be examined in the execution phase. If the learning application involves then cluster analysis and data clustering algorithms will be part of the ML data model used here. If the learning is supervised, data training algorithms will be involved as well. When starting with ML, the experience can be gained by obtaining a few common algorithms either supervised or unsupervised from the marketplace and deploying them in the cloud with some data to perform experiments.

*Execution.* Once the data is prepared and algorithms have been modelled to solve a specific business problem, the stage is set for ML routines to be run on the execution portion of the architecture. The ML routine will execute repeatedly as cycles of experimentation, testing and tuning are performed to optimize the performance of the algorithms and refine the results in preparation for the deployment of those results for consumption or decision-making.

*Deployment.* ML output is similar to any other software application output. ML output is persisted to dashboards that alert a decision-maker of a recommended course of action. When operationalizing ML programs, note that the learner becomes an analytics program, similar to any other analytic program it might run in production. Deployed outputs could take the form of reported insights, new models to supplement data analytics applications or information to be stored or fed into other systems. An important consideration here is the architecture need to be operationalized.

The ML architecture defines the various components involved in the machine learning cycle and involves the major steps being carried out in the transformation of raw data into training data sets capable for enabling the decision making of a system.

### *H. Machine Learning with Data Lake*

Predictive analytics and ML require access to diverse data sets and powerful, scalable compute resources. They enable financial organizations to leverage large amounts of data from social media, online journeys, the IoT and other sources to enable data-driven decisions across an organization. Leveraging a Data Lake to store the necessary information for powering predictive analytics and ML workloads empowers staff across an organization to analyse data, test theories and drive changes to business processes, the customer experience and products.

A Data Lake is an integration point between existing data platforms, to enable a seamless view into all of FSI's data. A Data Lake will complement existing systems by ensuring that analytical workloads, development, testing and ML model creation will not affect production workloads in other performance-optimized systems. Data Lake is a concept that supporting business and operational systems.

Applying ML for any practical use case requires a good knowledge of ML principles and technology a strong and deep knowledge of business and IT architecture and design aspects. The scope and aim of this ML for financial organizations is to enable us to create a better and faster solution ML driven financial systems and applications. The literature on ML systems revealed several methods of massive data analysis. It is found ML architectures that deal with structured and semi-structured data.

### *I. Literature Review*

Important ML techniques were discussed and areas where they were successfully applied. Based on these examples, it forecast hypothetical uses of ML in the realm of building design [5].

The requirements, benefits and pitfalls of ML architecture and how to get started are discussed [6].
A multi-tier architecture for sentiment classification [17] was proposed for Sentiment Analysis, which includes modules such as tokenization, data cleaning, pre-processing, stemming, updated lexicon, stopwords and emoticon dictionaries, feature selection and machine learning classifier. The sentiments of a large number of tweets generated from Twitter in the form of Big Data have been analysed using ML algorithms.

The research is focused on coffee machines located in common spaces where people usually do not care about saving energy [8]. The proposed approach lets the kinds of appliances report their usage patterns and to process their data in the Cloud through ARIMA predictive models. The aim of such prediction is that the appliances get back their next-week usage forecast to operate autonomously as efficient as possible. The underlying distributed architecture design and implementation rationale are discussed.

DataStax [9] offered guidance for system architects and administrators during the planning stages of development, test and production environments, whether in-house or at a private or public data centre. It explores common scenarios and configuration options for various deployments.

IoT devices produce massive amounts of data and ML requires heavy processing. Embedded devices usually have several sensors attached, and they are in turn connected to Gateways that route traffic from multiple devices. A typical stream processing pipeline chews crunches and enriches the raw payload in several steps, and there are some serious data on processing. Within a few hundred milliseconds of the time the original message was recorded, the results are available in live view that can be shown in a reporting dashboard. A ML Web Service is hooked to the stream processor and performs predictive analytics that becomes part of the live output. This is the canonical way of consuming machine learning models in stream processing platforms. It is central to both the major standard architectures (Lambda and Kappa) for these types of systems [12].

It is constructed ADVISOR, a two-agent machine learning architecture for intelligent tutoring systems (ITS) [14]. The purpose of this architecture was to centralize the reasoning of an ITS into a single component to allow customization of teaching goals and to simplify improving the ITS.

 

It sis described a wide range of heuristics including a novel one inspired by reinforcement learning techniques for propagating rewards through a graph which can be used to affect a search engine's rankings [15]. They demonstrated a system, which learns to combine these heuristics automatically, based on feedback collected unintrusively from users, resulting in many improved rankings.

ML applications in architecture are illustrated in research [8]. It complements those studies by hypothesizing on alternative applications of ML techniques that might influence the architectural practice.

It is illustrated the application of cognitive science principles to hard AI problems in ML and they proposed the LIDA technology, a cognitive science-based architecture capable of more human-like learning [21].

The stock prediction and ML architecture [25] supports an optimization process that is driven by predictive models. It has three basic components. First, incoming, real-time trading data must be captured and stored, becoming historical data. Second, the system must be able to learn from historical trends in the data and recognize patterns and probabilities to inform decisions. Third, the system needs to do a real-time comparison of new, incoming trading data with the learned patterns and probabilities based on historical data. Then, it predicts an outcome and determines an action to take.

A big data reference architecture for e-Learning analytical systems [26] had designed to make a unified analysis of the massive data generated by learning actors. This reference architecture made the process of the massive data produced in big data e-Learning system.

A network analytics architecture stack [27] had proposed to offer an analytics solutions architecture. This had been designed with a set of architecture principles that are commonly accepted as best practices in the network industry. With this architecture, it strongly believed that it could improve agility, while at the same time having control over data integration and distribution.

The existing literature deals with several ML models and architectures that tackle both structured and unstructured data.

### *J. Motivation*

In FSIs, fraud detection is a challenging problem. The fact is that fraudulent transactions are rare. They represent a very small fraction of activity within an organization. The challenge is that a small percentage of activity can quickly turn into big dollar losses without the right tools and systems in place. Criminals are crafty. As traditional fraud schemes fail to pay off, fraudsters have learned to change their tactics. Most FSI still use rule-based systems as their primary tool to detect fraud. Rules can do an excellent job of uncovering known patterns; but rules alone are not very effective at uncovering *unknown schemes*, adapting to new fraud patterns, or handling fraudsters' increasingly sophisticated techniques. ML is a best solution for fraud detection.

For fraud detection, ML combines a variety of supervised and unsupervised methods in one system to be more effective than any single method alone. This is where ML becomes necessary for fraud detection. An effective ML solution requires scalability and elasticity. The exact composition of an ML solution will vary, depending on the ML algorithms, how much automation needs to be built into the system, and which frameworks and tools are being used. An ML solution enables businesses to gain scalability, effectiveness and efficiency.

Hence, the objective of this research article is to introduce the ML approach to FSI. The proposed solution includes the ML model and architecture to financial services institutes.

### *K. Major Contribution*

Building a ML solution can be complex. There are many use cases, technologies, and tools available. The major contribution of this article is a detailed discussion of the ML model and architecture design to FSI [6]. This research article makes the following contributions:

a. It introduces ML and real-time analytic technology to large-scale financial applications.
b. It designs an ML model and architecture that leverages state-of-the-art Big Data technology to FSI.
c. The proposed ML model and architecture provides insights into optimal design and deployment strategies to FSI.

This research article is intended to be used as an architecture who are defining, deploying and integrating ML solutions into FSI. It describes an architecture that will support a productive proof of concept, experimental application, and sustain growth into production as a multitenant system that can continue to scale to serve a larger financial organization while integrating into the existing IT infrastructure. The performance evaluation demonstrates the scalability for the best design choice.

## III. METHODOLOGY

The methodology followed to design ML architecture to financial organizations is depicted below. In the last decades, computational advances changed the way architects design. Nowadays, computational approaches are fully embedded in the architectural practice. There are some ML applications in architecture that might affect the architectural practice. Those proposed ML applications envisage the improvement of existing design tools, by using ML to allow a more efficient and informed design process. ML shows large potential for enhancing the design process since some of its learning algorithms resemble reasoning processes that are frequently applied by architects such as abductive reasoning [30]. ML have a broad impact in architectural practice with the aspects of conceptualization, algorithmization, modelling and optimization:

a. *Conceptualization*, which includes conceptual definition, approach, and exploration by the designer.
b. *Algorithmization*, which consists in developing and implementing a computer program capable of representing and instantiating the applied concepts.
c. *Modeling*, which encompasses the tasks of analytical modeling for visualization. ML has the potential to enhance design activities related to the generation of building models, particularly, analytical models for building performance, visualization and documentation.
d. *Optimization*, which is due to the demand for sustainability and efficient use of resources in the built environment, as well as by the emergence of different ready-to-use toolsets. One of the difficulties of performance-based design is the identification and fine-tuning of the best optimization algorithms for a given design problem.

The above methodology is applied to FSIs and designed an ML architecture, which is discussed in the next section. The high-level structure in the exhibit above represents a layered architecture that has been applied successfully by many financial organizations, across many industries, especially in finance. It extends to accommodate new digital capabilities such as collecting and analysing unstructured data, enabling real-time data processing and streaming analytics.

## IV. RESULTS & DISCUSSION

This section describes the proposed ML architecture that enables FSI use cases. The FSI need leading-edge architecture, with advanced technologies, new solutions and flexible structures that can store and analyze huge amounts of different types of data to extract useful insights and generate value across the enterprise.

To apply ML approach for the business for real, it should develop a solid architecture. A good architecture covers all crucial concerns like business concerns, data concerns, security and privacy concerns. Besides, of course, a good architecture should address technical concerns to minimize the risk of instant project failure. Creating a good architecture for new innovative machine learning systems and applications is an unpaved road. A good architecture on machine learning should help us in several ways.

### *A. Conceptualization*

The conceptualization tasks are essential at early design stages and consist in the definition of the main ideas, strategies, and spatial and temporal narratives of a specific design.

*Goals.* The goal of ML architecture is to help businesses access, analyze and visualize data, and then communicate those insights in meaningful dashboards and metrics. Besides, those that provide a more comprehensive solution, tend to lack the features that make it user-friendly.

Data reporting analytics provides FSIs with a centralized and transparent view of the business. It enables them to identify improvement areas. Typical examples in banking include suspicious activity reporting, transaction monitoring, etc. The different types of analytical offering and supports them with a few prevalent business use cases in the proposed ML architecture are detailed below.

- *Descriptive analytics* aims at generating actionable insights on the current business situation using complex data being captured from multiple sources. Analytical reports can be used for root cause analysis with various levels of drill down by attributable dimensions. Typical examples in banking include customer segmentation and profitability analysis, campaign analytics, etc.
- *Predictive analytics* includes predicting the likely future outcome of events often leveraging structured and unstructured data from a variety of sources. These are more specific one-off business use cases that aim to solve a high impact business problem using data from multiple sources. Typical examples in banking include pattern recognition and machine learning to predict fraud, generating risk alerts at customer/ product/geography level, designing personalized and next-best offers and trigger-based cross-sell campaigns, etc.
- *Prescriptive analytics* include prescribing action items required to deal with predicted future events using data from a variety of sources. This includes simulations in various business scenarios. Prescriptive analytics can prepare banks for changing economic and customer trends. It also provides management teams with better insights that could help them alter the expected outcomes through changes in strategy, programs, policies, and practices.
- *Real-time analytics* can leverage to drive value is streaming analytics for real-time monitoring, mathematical optimization techniques for finding the optimal strategy, simulation models to test a new idea. In addition, advanced analytics and machine learning techniques are used to identify customer behaviours and transactions that are most likely to generate suspicious activities.

 

The quality attributes for ML systems are interoperability, modifiability, portability, usability, reusability and integrability. ML Systems are required to interoperate with each other or other systems. They need to be easily modifiable and extensible, so that they can be adapted to emerging technologies and pedagogical models and thus increase their lifetime. They need to be portable to multiple clients, so that their users can operate them through an interface. In addition, the other qualities are security and availability.

*Design principles.* The proposed ML architecture is technology agnostics. The design principles are statements of direction that govern selections and implementations. They provide a foundation for decision-making. In addition, they are commonly used within business design and successful IT projects. The key principles that are used for the proposed ML architecture are presented below.

1. To address the most important ML aspects, the quality aspects such as security, privacy, safety, and all ML architecture building blocks.
2. To translate the ML architecture building blocks to solution building blocks.
3. To outline the conceptual architecture building blocks that make an ML architecture.

ML architecture principles are used to translate selected alternatives into basic ideas, standards, and guidelines for simplifying and organizing the construction, operation, and evolution of systems. The important concerns for the proposed ML architecture are the aspects of business, information, ML applications and frameworks, hosting, security and safety, maintenance, and scalability, flexibility and performance.

- The business aspects include business capabilities, business processes, legal aspects, risk management.
- The information aspects include data gathering and processing.
- ML applications and frameworks needed (e.g. type of algorithm, ease of use)
- The hosting includes computing, storage and network requirements.
- The maintenance includes logging, version control, deployment and scheduling. The other aspects include scalability, flexibility and performance.
- The security includes privacy and safety aspects.

*Requirements*. The requirements considered when identifying the ML architecture are sources of data, data sets, data formats, latency of data, volume of data, data delivery modes, multi-platform data architecture, agile delivery method, use of traditional platforms, data virtualization techniques, well-defined extract-transform-load (ETL) or extract-load-transform (ELT), analytics use, support for all types of users, flexibly and quickly, adapt to change, etc. The modern analytical requirement needs an architecture mix of traditional approach for sustainability and ability to cater for a fast-paced business depends on data analytics, which is, must for business to survive and become a data-driven decision-making organization.

The requirements are identified and carried out to design ML architecture to FSIs. This leads to some functional and non-functional components of the architecture and finally to the ultimate design of the high-level architecture of the system. They are discussed below.

- *Abstraction.* It prefers higher-level abstraction, which the workload on programming is minimum.
- *Affordability.* It affords guaranteed data processing without losing any information.
- *Fault-tolerance.* The servers have to be fault-tolerance.
- *Real-time.* The model received from batch training can be loaded into the real-time layer to achieve real-time classification and predictive analytics.
- *Scalability.* The data analytics engine grows with fewer efforts as the data grow bigger and bigger

The non-functional requirements and constraints are thus investigated and they are the volume of data, processes or management challenges.

- *Aggregation.* There is a big quantity of data to be aggregated or integrated.
- *Analyze.* It is a challenge to analyze the semi-structured information available. Thus, analysis and modelling are to be considered a requirement of the architecture design.
- *Data acquisition.* The data acquisition is the crucial process to be performed. Acquiring the right data correctly is thus a main requirement of the design.
- *Data Cleaning.* This process is meant as developing and maintaining an extraction method that mines out the required information from unstructured data.
- *Security.* Security is certainly a big concern and top requirement for the ML Architecture.
- *Volume.* The volume and type of data are considered a challenge for the ML architecture to be developed.

FSI gather sensitive data that in the wrong hands could lead to liability claims and worse. Therefore, securing access to the data, regardless of data management platforms, tools, and data transmission methods used, is critical. *Data governance* needs regarding the meaning of data as well as its accuracy and quality will often require close coordination with and among multiple lines of business.

*Quality Factors*. Regardless of the technique used to elicit the requirements, the desired qualities of the business system to be constructed determine the shape of its structure. The architectural qualities considered the proposed architecture are listed below:

 

- *Deployability.* It should be easily deployable.
- *Interoperability.* It has a single interface for all business analytics capabilities with the ability to navigate through scorecards, dashboards or reports.
- *Leverage existing infrastructure.* It is designed to support existing environments and leverage everything those environments have to offer Web infrastructure, databases and OLAP data sources, security providers, application servers and more.
- *Manageability.* This architecture can administer efficiently and proactively ensuring that potential problems are identified early and avoided, thus keeping the system operating effectively.
- *Reliability.* This architecture supports operating on a 24x7 basis with redundancy for all capabilities and services.
- *Scalability.* This architecture linearly supports scalability to thousands and millions of users across a global organization.
- *Security.* This architecture supports existing security providers to ensure that access to both the business analytics system and the information in that system is always secured as required.
- *Usability.* This analytics architecture recognizes and accommodates different types of business users through common user experience, across all business analytics capabilities and on the full range of technology, including mobile devices.

The above a set of attributes or qualities are considered in the proposed architecture. Some qualities are easier than others to describe in terms of standards are.

B. *Algorithmization*

Algorithmic approaches to architectural design are becoming increasingly popular among architects. The algorithmic approaches to FSI is explained below:

*Business Services.* Financial analytical services can help to understand the business' past and present performance and make strategic decisions. Some of the critical financial analytical services are predictive sales analytics, client profitability analytics, product profitability analytics, cash flow analytics, value-driven analytics, consumer analytics, market analytics and shareholder value analytics.

1. *Cash Flow Analytics.* It needs a certain amount of cash to run the business organization on a day-to-day basis. Cash flow is the lifeblood of any business. It involves the use of real-time indicators and predicts cash flow using tools like regression analysis. Cash flow analytics can also help supporting a range of business functions.
2. *Client Profitability Analytics.* Every business organizations needs to differentiate between clients that make them money and clients that lose them money. By understanding the customers' profitability, it will be able to analyze every client group and gains useful insight.
3. *Customer Analytics.* Customer analytics is the systematic examination of a company's customer information and customer behavior to identify, attract and retain the most profitable customers. Customer analytics comprises the backbone of a business' marketing strategies and integrates advanced techniques like data visualization, predictive modeling, information management and segmentation.
4. *Market Analytics.* Marketing analytics enable marketers to evaluate the success of their marketing initiatives. This is accomplished by measuring performance through blogging, social media and channel communications. Marketing analytics uses important business metrics, such as ROI, marketing attribution and overall marketing effectiveness.
5. *Predictive Sales Analytics.* Sales revenue is critical for every business. A predictive sales analytics involves coming up with an informed sales forecast. Predictive sales analytics can help sales manager plan and manage the business' peaks and troughs.
6. *Product Profitability Analytics.* Product profitability analytics can help the organizations the profitability of every product rather than analyzing the business as a whole. It can also help to establish profitability insights across the product range so you can make better decisions and protect your profit and growth over time.
7. *Shareholder Value Analytics.* Shareholder value analytics calculates the value of the company by looking at the returns it is providing to shareholders. Shareholder value analytics is used concurrently with profit and revenue analytics.
8. *Value-Driven Analytics.* Most business organizations goals can be formal and listed on a strategy map that pinpoints the business' value drivers. These value drivers are the vital drivers that the organization needs to pull to realize its strategic goals. Value driver analytics assesses these levers to ensure that they can deliver the expected outcome.

The above financial services encompasses a broad range of businesses that manage money, including banks, credit card companies, insurance companies, consumer-finance companies, stock brokerages, investment funds, and some government sponsored enterprises.

*C. Machine Learning Model*

ML and advanced analytics help businesses understand current and past performance, predict future performance and make smarter decisions. The different available ML models are sentiment analysis, handwritten recognition, translation, classification, style transfer, music tagging, predicting text, etc. Choosing a proper ML model for a particular use case is very important to obtain the proper result of an ML task. Evaluation metrics or KPIs are defined for particular business problems and the best model is chosen for production after applying the statistical performance checking. The proposed ML model to FSI is shown in Figure 6.

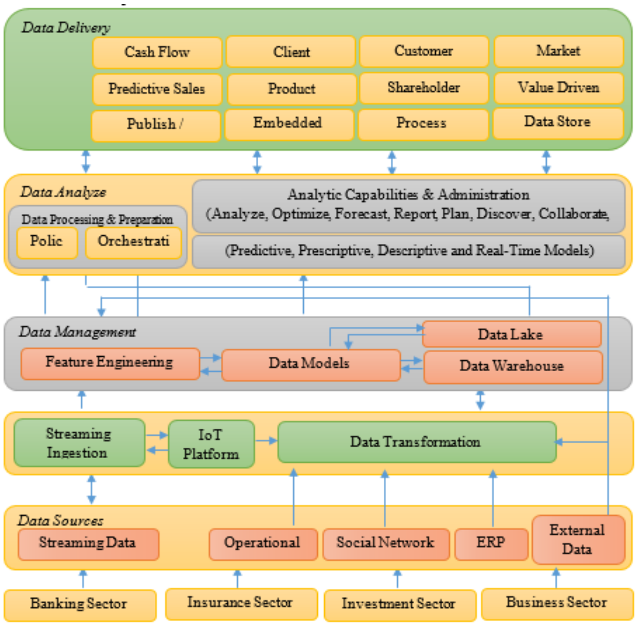


Figure 6. Proposed ML model to FSI

Finance services and their related data is being generated in unprecedented quantities by businesses, sensors, financial applications, social networks and so on. Once data is generated and stored, it is usually used for two primary purposes. First, the data is used in a transactional or operational sense. Data records are created, read, updated, and deleted as needed to support a given application and its user's intended interactions. Second, the data is used to extract useful information and actionable insights, make predictions and recommendations, identify patterns and trends, drive business decisions, Track and report key KPIs and much more.

*Data Storage.* All generated financial data must be stored. The data storage systems are usually classified as being either relational (RDBMS), NoSQL, or NewSQL. This designation is made based on the data model, physical storage strategy, query language, querying capabilities, CAP trade-offs, and so on. Databases can also be further classified by their usage in an overall solution. The common data storage classification are Operational data store (ODS), Data Warehouse, Data Lake, Data Mart, OLAP and OLTP/TDS, Master data store, In-memory, File system, Distributed file system (e.g., HDFS, etc. Some of these systems are better suited for transactional and event-driven data storage (e.g., OLTP), while others are more analytics focused (OLAP, data warehouse, etc.).

Each type of storage typically involves one or more finance data models. The finance service data model describes the virtual representation of the data, as opposed to the physical representation and storage of the data, which is handled by the data management system. Typical data models and schemas include Relational for RDBMS systems, NoSQL, NewSQL, Data Warehouse and OLAP.

*Data Acquisition.* Financial data can be acquired and collected in many different ways, including physical sensor measurement (IoT), financial software transactions and events, server logging, Blogs, finance news, social networks and mobile app usage tracking, and so on. The acquired financial data is usually stored in a data storage system (i.e., database) of some sort, and may need to be ingested into a data pipeline and ultimately another data store (e.g., data warehouse). The financial data may also need to be combined (integrated) with data from other sources as well. Once data has been generated physically by sensors or by software code, data can be ingested into a database or data pipeline in a variety of ways.

Once financial data is stored, financial applications and/or business users will likely need to access it. The most important requirements of a data system are availability, performance, and scalability. These three requirements are related and have impacts on one another.

*Data Processing.* Data processing is a stage of the data pipeline that involves data cleaning, dealing with missing or bad values, transformations, metrics calculations, and so on. Typically, data processing is categorized as either batch, real-time, near real-time, or streaming.

- *Batch processing* involves processing data in a batch either as a single job or as recurring process, and is not usually a very fast process depending on the amount of data involved.
- *Real-time processing* deals with processing data as it moves through the data pipeline in real-time, and often the data moves directly from the processing stage into visualization, persistent storage, and/or as a response to a request. Real-time processing is characterized by very fast processing where minimal time delays are critical. Near Real-time processing on the other hand, differs in that the delay introduced by data processing and movement means that the term real-time is not quite accurate.

The data processing stage can be accompanied by a data movement stage, which is usually called ETL/ELT depending on the situation. In the case of ETL, data is extracted from one or more data sources, often loaded into temporary storage (staging), transformed by processing logic, and then loaded into the data's final storage place. The final data store is usually a data warehouse, data lake, OLAP system, or analytics database of some sort.

 

*Data Access.* Most financial data contain very useful information that can be extracted in order to gain actionable insights, drive business decisions, and make predictions and recommendations, and so on. Financial data is typically accessed by creating a connection to a data store, querying the data (e.g., using SQL) to retrieve a specific subset of it, and then finally performing analytics of some type on the data. Analytics can be in the form of statistical analysis, data visualization, machine learning, artificial intelligence, predictive analytics, and so on.

BI refers to the extraction of useful information from data to drive business decisions that help achieve business goals. Usually BI is carried out using a so-called BI tool, which is software that can connect to different data sources in order to query, visualize, and perform analysis on data.

The described analytics tasks depend on the complexity (statistical, mathematical, and algorithmic), and amount of computer programming required. Usually finance analyst and data scientists perform very technical analytics tasks that require significant programming; whereas roles with a variation of an analyst title (e.g., data analyst) usually leverage business, intelligence tools (Excel, Tableau, Looker, etc.).

*D. ML Optimization*

To explore the myriad methods and techniques for ML model optimization across the lifecycle, it has collected several helpful optimization strategies. They include handling data, architecture selection, model debugging, ML model visualization, ML model evaluation and selection, hyperparameter tuning, optimization algorithms, and more

- *Handling Data.* The data pipeline starts with collecting the data and ends with communicating the results. Data pre-processing is one of the important steps. It includes cleaning, Instance selection, normalization, transformation, feature extraction and selection, etc. The product of data pre-processing is the final training set.
- *Architecture Selection.* It selects the best architecture for financial organizations.
- *Model Debugging.* It covers the basics of bias-variance trade-off in financial organizations and presents regularization techniques to improve model performance.
- *ML Model Visualization.* It visual representation technique to intuitively understand their outputs.
- *ML Model Selection and Evaluation.* A re-examination of the growing assumption that working with pre-trained models results in higher model accuracy.
- *Hyperparameter Tuning, Optimization Algorithms, and More.* It demystifies the meaning of hyperparameters, understanding their importance, and optimizing and fine-tuning them.

*E. Machine Learning Architecture*

The stages discussed in Figure 4 map to the basic architecture that will be needed to execute ML in the enterprise. This architecture differs in many ways from the architectures used for traditional data processing and analytics functions in enterprises. ML architecture needs to be more flexible to accommodate the elastic learning patterns of the ML process and the large and varying volumes of data and processing power involved. It covers the following infrastructure areas for functions needed to execute the ML process:

- *Data acquisition,* where data is collected, prepared and forwarded for processing
- *Data processing,* where steps such as preprocessing, sample selection and the training of datasets take place, in preparation for execution of the ML routines:
- *Feature engineering* (a subset of the data processing component), where features that describe the structures inherent in your data are analyzed and selected
- *Data modelling* or model engineering, which includes the data model designs and machine algorithms used in ML data processing (including clustering and training algorithms):
- *Model fitting,* where a set of training data is assigned to a model to make reliable predictions on new or untrained data
- *Model evaluation,* where models are evaluated based on performance and efficacy
- *Execution,* the environment where the processed and trained data is forwarded for use in the execution of ML routines (such as experimentation, testing and tuning)
- *Deployment,* where business-usable results of the ML process — such as models or insights - are deployed to enterprise applications, systems or data stores (for example, for reporting)

It is designed an ML Architecture to support ML applications, technical professionals must envision a revitalized data and analytics end-to-end architecture that incorporates diverse data, models and algorithms and can deliver analytics. Figure 6 derived from Figure 4 shows four-layer architecture that includes ML capabilities to FSIs.

*Data Source Layer.* This layer is also called a data acquisition layer. The data source involves data collection, preparing and segregating the case scenarios based on certain features involved with the decision-making cycle and forwarding the data to the processing unit for carrying out further categorization. This stage is sometimes called the data pre-processing stage. The data model expects reliable, fast and elastic data, which may be discrete or continuous in nature. The data is then passed into stream processing systems (for continuous data) and stored in batch data warehouses (for discrete data) before being passed on to data modelling or processing stages.

 

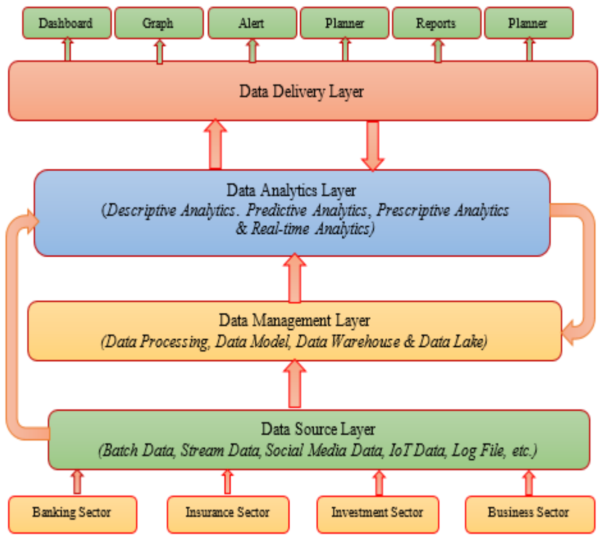


Figure 6. Proposed ML Architecture to FSI

*Data Management Layer*. This layer is also called data organize layer. The received data in the data acquisition layer is then sent forward to the data processing where it is subjected to advanced integration and processing and involves normalization of the data, data cleaning, transformation, and encoding. The data processing is also dependent on the type of learning being used. E.g., if supervised learning is being used the data shall be needed to be segregated into multiple steps of sample data required for training of the system and the data thus created is called training sample data or simply training data. Also, the data processing is dependent upon the kind of processing required and may involve choices ranging from action upon continuous data which will involve the use of specific function based architecture, for example, lambda architecture, Also it might involve action upon discrete data which may require memory-bound processing. The data processing defines if the memory processing shall be done to data in transit or rest.

*Data Analytics Layer*. This layer involves the selection of different algorithms that might adapt the system to address the problem for which the learning is being devised. These algorithms are being evolved or being inherited from a set of libraries. The algorithms are used to model the data accordingly; this makes the system ready for execution step. This stage in machine learning is where the experimentation is done, testing is involved and tunings are performed. The general goal behind being to optimize the algorithm to extract the required machine outcome and maximize the system performance. The output of the step is a refined solution capable of providing the required data for the machine to make decisions.

*Data Delivery Layer*. This layer is also called a data deployment layer. In this layer, ML outputs need to be operationalized or be forwarded for further exploratory processing. The output can be considered as a non-deterministic query, which needs to be further deployed into the decision-making system.

*Monitoring*. The proposed architecture includes monitoring capabilities can help with finance model optimization efforts. *Security*. The data security is paramount to a mature ML architecture. Security includes authentication, authorization, and encryption. It must apply authentication and access controls across the entire framework, from ingestion to report delivery.

According to IEEE 1471-2000 standard [29], layered frameworks and models for enterprise architecture have proved useful because layering has the advantage of defining contained, non-overlapping partitions of the environment. The proposed architecture and design of the financial organizations have the following advantages over monolithic architecture:

- *Easy support*. This architecture and model is easier to support for new types of customers or clients.
- *Efficiency*. This architecture highly supports modular development of the financial application.
- *High scalability*. The architecture is highly scalable. The end-users and their view can grow as the model grows and older versions of the views shall be used as long as a common interface is maintained.
- *Maintenance*. The architecture and model support easier maintenance of the code and future improvements of the financial application.
- *Multiple views*. The separation of model and view allows multiple views to use the same financial application model. This does not only facilitate the easier implementation of enterprise model but also easier to test, and maintaining of the enterprise application.

The proposed layered architecture provides reuse of the functionality, improve performance, scalability and maintainability, and provides security.

*Architecture Design Challenges*. To use the financial data effectively, it requires the right data analytics architecture that built on a foundation of business requirements [4]. However, most business companies take a technology first approach, building major platforms while focusing too little on killer use cases. Many businesses, seeing digital opportunities in their sectors, rush to invest without a considered, holistic data strategy. They either focus on the technologies alone or address immediate, distinct use cases without considering the mid-to-long-term creation of sustainable capabilities. The survey found the second-largest challenge, companies face is designing data architecture and technology infrastructure that effectively support data and analytics activities at scale.

While the potential business value of ML is clear, FSI faces several challenges when beginning their ML journey. Overcoming these challenges is the key to digital transformation and taking full advantage of data. Some of the most pressing challenges associated with deploying ML include *data often exists in silos, data is constantly changing, privacy and ethical issues must be addressed and finding the right talent can be difficult.* ML typically requires strong mathematical and statistical skills if a solution is going to go beyond an off-the-shelf algorithm or a packaged set of APIs.
Model selection is one of the most difficult aspects of building a ML solution. For all the science and match baked into ML applications, model selection remains a highly subjective task that relies on the opinions of experts. For any given scenario, the number of machine learning models that can solve it is incredibly large so it can able to know the most optimal model for the job. Furthermore, the more accuracy is needed for a ML problem the more time is spent in the model selection process. Hence, the process of selecting and designing a ML model is an extremely time-consuming exercise.

*Evaluation of the Architecture.* The proposed architectures can be evaluated according to specific criteria and are designed to fulfil the above quality attributes. The evaluation techniques do not assess the quality characteristics of products but measure the architecture's ability to satisfy them. The evaluation used for the assessment of the proposed architecture with respect to the quality attributes is comprised of a combination of scenario-based evaluation and architectural prototype evaluation. The scenario-based evaluation, which is based on creating a set of scenarios, in order to evaluate a specific quality attribute. For example, the interoperability quality can be evaluated by creating scenarios of exchanging data between the system under development and other systems, and evaluating the level of success in these interoperations. The architectural prototype evaluation, which is based on implementing only some of the parts of the architecture while the rest are ignored.

In addition, there are run-time qualities and development qualities. The run-time qualities are performance, security, availability, functionality and usability. The development qualities are modifiability, portability, integrability, interoperability, reusability, testability. The evaluation in most of the cases was qualitative and not quantitative as there are no metrics yet for these techniques. It examines the architectural prototype, which is an implementation of the software architecture instance. Therefore, the results from the evaluation can be attributed to the proposed architecture, if and only if they do not rely on implementation decisions. The layered nature of the system supports modifiability and modifiability but diminishes performance.

## V. DISCUSSION & RESULTS

Big Data and ML have completely transformed several industries including financial organizations. The combination of large amounts of data and ability to analyze that data to develop new narratives, it can now manage risk much more effectively and identify new sources of value for investors and other financial market consumers.

The adoption of big data technologies and capabilities to extract insights and add value from newly available data is bringing change to business analyst roles within financial services organization. The timely availability of large amounts of financial data allows decisions to be made on evidence-based analysis rather than intuition. This makes the decision makers to cost reduction and revenue growth. New technologies such as process automation and cloud storage enable firms to handle huge volumes of unstructured data at lower cost. This shifts the focus of decision making to the business units. FSI are facing increased regulatory reporting demands, requiring improved infrastructures and procedures. This is fostering closer collaboration and integration as well as better capabilities for conducting required activities such as real-time simulations.

Sven Blumberg, 2017 reported that doing the technology first produced more problems than successes, including redundant *and inconsistent data storage, overlapping functionality and a lack of sustainability*. These problems have real business consequences. Meeting leading-edge business requirements, such as real-time customer and decision support, and large-scale analytics requires the integration of traditional Data Warehousing with new technologies.

This article will help the financial organizations outline an architecture, founded on the best practice analytics model, that would enable the capabilities the organizations desired and assess available solutions. The proposed architecture allows the organizations for large storage, distributed processing and frequently unstructured data sets across thousands of individual machines. This was especially useful in scaling the financial organizations high-frequency requirements for its online fraud-detection processes [10]. In this way, the financial organizations achieved its primary business goals. It added new, differentiating capabilities, such as real-time analytics, and created real enterprise value with a relatively small technology investment. Today, the banking sector is considered the leader in financial data analytics in its market and sells analytics services to other financial institutions. It started with a clear view of its business goals, technology selection, and created an analytics architecture that worked.

 

## VI. CONCLUSION AND FUTURE ENHANCEMENT

Financial services firms have long been dependent on data and analytics technologies to maximize opportunity and minimize risk. The recent explosion of new types and sources of data has put tremendous pressure on banks, insurance companies, capital market and other firms, which must harness this Big Data to keep pace with the competition. Many FSI have turned to collect and manage diverse volumes of unstructured and semi-structured data alongside traditional repositories like the enterprise Data Warehouse. Firms that have adapted to the challenge of Big Data are using it to better serve customers, minimize risk, enhance financial management, and develop innovative new business models.

In this article, the architectural design of finance data analytics is presented. The multi-tiered architecture of the proposed system is presented with associated components in each tier. In addition, the advantages of the proposed architectural design framework are envisaged. Maximizing computing power, real-time, AI, lowest cost and introducing the blockchain technology to financial services will be some of the proposed work for future.

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### Authors Profile


Mr. K. Palanivel has completed his Master Degree in Computer Science & Engineering from Bharathiar Pondicherry University, Pondicherry, India during 1998. Prior to this, he received her Bachelor's in Computer Science & Engineering University, Tamil Nadu, India during 1994. His research coverage includes software architecture, e-Learning, analytics and Web Services Technology. He is working as Systems Analyst and responsible for driving the unit of Campus Network monitoring and presence at Pondicherry University.


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