

MODERNIZING ACTUARIAL PROCESSES WITH DATABRICKS: LEVERAGING DATA LAKES AND ADVANCED ANALYTICS FOR PREDICTIVE MODELING**Nihar Malali****Senior Solutions Architect, UT Dallas**

ABSTRACT

Modernization has become a top priority for the actuarial business since it needs better tools to work with information and make decisions at greater speed. Most old actuarial systems using several outdated data sources plus complex models slow down their risk evaluation work and create issues in claims predictions and insurance rate development. This article looks at how Databricks's advanced analytics platform with database storage and machine learning features helps update actuarial workways and builds better risk forecasting.

Actuarial teams at Databricks can store and process all data types in one platform which lets them combine datasets from across their organization into a scalable data storage system. This method helps us locate data more easily while making the database management system work faster and stronger. Databricks teaches actuaries how to build advanced models through artificial intelligence that help spot better risks and spot price changes while spotting wrong transactions. Real-time data processing helps insurance businesses make quicker data-based choices while monitoring industry movements and new threats. The article provides details about how to transport actuarial teams towards Databricks-based work operations by presenting specific ways to switch from existing systems and train staff in cloud data science. The article explains how AI machine learning will enter the market alongside IoT data tracking systems and blockchain ecosystems for managing insurance data records.

Databricks and new analytics tools help insurance companies succeed better by running with higher efficiency while keeping exact predictions and staying compliant under latest regulations. This article provides step-by-step guidance for actuaries wanting to update their systems while using advanced technology to develop new risk protection solutions.

Keywords:

Actuarial Processes, Databricks, Data Lakes, Advanced Analytics, Predictive Modeling.

1. INTRODUCTION

Actuarial science supports practical risk control efforts and performs best at insurance companies. It analyzes risk situations through mathematics and statistics to control safety margins. Actuary work depends more on using data to make smart business decisions so actuaries examine large databases to predict future market direction and price insurance products with risk evaluation included. The increasing need to use data depends on better ways to compute results and handle data better (Li et al., 2017).

Actuarial professionals encounter multiple critical issues with their normal work procedures. Legacy business systems work slowly while dealing with big amounts of data and run less effectively because stored information remains separated between many platforms. The restrictions on data access and viewing slow the time to make decisions effectively. Limited data speed and disorganized data sets create modeling issues especially when insurance requires quick changes (Raghavendra & Bheemanagouda, 2019). The integrated analytics platform Databricks successfully solves the problems encountered by insurance engineers. It offers one system that handles big data efficiently while teaching it to learn and change data results. Databricks utilizes cloud data lakes and distributed systems to help actuaries process big data fast so they can make better and expedited predictions according to Vernik et al. (2017). The platform lets teams work together online to exchange data successfully and remove department walls which enhance their work process.

Through this article we study how Databricks and combination of data lakes and advanced analytics affect actuarial predictive modeling. These technologies serve actuaries who need better solutions to handle typical work issues while making smarter choices using vast datasets (Eichler et al., 2021; Shirke et al., 2017).

2. CHALLENGES IN TRADITIONAL ACTUARIAL PROCESSES

The traditional actuarial data management system requires changes because it struggles to process data efficiently in a digital environment. Upgraded technology platforms together with scattered data sources and slow processing affect these normal operations.

2.1 Dependence on Legacy Systems

Actuarial experts depend on old databases and Microsoft Excel to work with and examine data even though these methods were designed long ago. The systematic tools that served us well in past times now show clear weaknesses especially when it comes to handling large volumes of data and fast computing. The research team found that established methods cannot handle present-day actuarial work because it needs faster data handling processes according to Li et al. (2017). Taken-together systems of previous technology and modern devices create challenging processes that increase the risk of mistakes and slow down the switch to faster actuarial work styles according to Raghavendra and Bheemanagouda (2019).

2.2 Data Silos and Fragmented Data Sources

Under the traditional actuarial setup data stays separated since each department stores it in their separate computer systems. Separate data sources make it challenging for the organization to find complete and accurate data when it needs them. The inability to exchange data across different systems makes data collection hard for actuaries to perform meaningful analysis according to Achieng (2017). Data preparations take up too much of an actuary's time which slows down important decision-making according to Xu and Xu (2018).

2.3 Computational Bottlenecks in Risk Modeling

Actuarial science relies heavily on on-premises computing systems which cause slow processing speed in risk modeling practice. Monte Carlo simulations and other mathematical models along with regressing data need strong computing resources to handle their big data processing demands. Current data processing methods have limited power which slows down essential operations. The lengthened processing time weakens the accuracy of analyses by compromising both pricing accuracy and detection of new risks according to Li et al. (2017). When data changes quickly or the market shifts the actuary cannot make accurate updates because their current system cannot analyze data in real-time (Raghavendra & Bheemanagouda, 2019).

2.4 Lack of Real-Time Insights

Actuarial processes based on traditional methods cannot deliver instant viewpoint analysis. Traditional systems need many hours to deliver information needed by actuaries for determining policy rates and claims modeling outcomes. Actuaries need more time with current systems to quickly adapt to market shifts as well as new cross-industry situations and developments (Sumasgutner et al., 2019). The actuarial industry requires real-time decision tools because predictive analytics demands faster results according to Shirke et al. (2017). Insurance companies must see fresh data in time to pursue new opportunities and handle arising risks effectively.

Standard actuarial techniques struggle to handle the present needs of insurance businesses today. The industry needs modern systems that handle many types of data by linking sources and speed up calculations to solve these current difficulties. Using modern technologies helps actuaries identify new risks and make their operations faster and more effective.

Challenge	Description
Dependence on Legacy Systems	Actuaries still use the conventional programs Excel and on-premises databases but these systems cannot handle substantial data quickly.
Data Silos & Fragmented Sources	Each department stores its data independently which makes it hard to process all the information properly.

Computational Bottlenecks	Basic hardware resources cannot handle modern risk analysis tasks which slow down all decision-making operations.
Lack of Real-Time Insights	Organizations need extended periods to produce reports through traditional procedures because they cannot update their strategies fast enough to match market fluctuations.

*Table 1: Challenges in Traditional Actuarial Processes***3. INTRODUCTION TO DATABRICKS AND DATA LAKES FOR ACTUARIAL SCIENCE****3.1 What is Databricks?**

Databricks creates an analytics platform that helps users prepare and work with big data effectively plus machine learning. The platform uses Apache Spark technology plus MLflow and Delta Lake components to support machine learning. This cloud system boosts processing speed which actuaries use to handle large datasets and generate precise models as reported by Databricks in 2017.

Actuaries use Databricks for their big data analytics because this platform handles every actuarial dataset type including claims information, risk element outputs, and estimated financial numbers. The addition of ML tools helps actuaries use improved prediction methods to make smarter decisions. Teams from various global locations can access and work with complex data much more effectively through our cloud infrastructure (Vernik et al., 2017).

3.2 Role of Data Lakes in Actuarial Data Management

A data lake serves as a single database that stores all types of data including both organized and disorganized big datasets. Data warehouses focus on pre-defined tables but data lakes can store multiple types of data including unprocessed files and different types of actuarial records according to Sawadogo and Darmont (2021). Many different types of actuarial science data can fit successfully into the flexible data lake storage solution.

Data lakes present better performance than standard data handling methods. Data lakes provide unlimited growth capacity because they are designed to handle large amounts of data in actuarial science as demonstrated by Eichler et al. in 2021. Depositing unprocessed data in the system helps actuaries preserve source data from various inputs prior to any necessary processing adjustments. The system allows researchers to work better with actuarial data by letting them explore diverse models and datasets. Having constant access to updated data helps our team generate prompt insights that support better risk assessments and insurance price decisions (Shirke et al., 2017).

3.3 How Databricks Enhances Actuarial Data Processing

Databricks simplifies actuarial data handling because it provides advanced data connection tools. The platform optimizes ETL strategies to make actuarial raw data workable for analysis and modeling. Using automation Databricks simplifies data transformation steps so actuaries can dedicate their time to advanced risk modeling and pricing work as mentioned by Shirke et al. (2017).

Databricks gives actuaries complete freedom to process streaming data for real-time use or batch processes data according to their needs. The streaming feature lets Databricks handle an uninterrupted flow of data from insurance claims and market trend sources before running quick analyses. Estimating claim trends and finding fraudulent claims requires this data analysis tool according to Li and colleagues (2017). The batch approach makes perfect sense when processing big datasets that need to run regularly but can wait for immediate analysis (Xu & Xu, 2018).

By connecting to Delta Lake Databricks strengthens both data security and management features. Delta Lake maintains data quality through its ACID transaction system plus schema controls and version records that defend against update errors. Actuarial uses depend heavily on this system because correct data helps business performance and obeys industry rules (Eder & Shekhovtsov, 2021). Through Databricks and Delta Lake technology users can make sure actuarial research uses accurate current data because these systems let you handle different data versions securely (Richards, 2017).

Through Databricks users can control how their actuarial data behaves and make their computations run faster within a cloud platform that teams data processing capabilities plus machine learning and security setups together. By

adopting this approach actuarial teams improve their data management system which then delivers dependable results for insurance and actuarial work.

Aspect	Traditional Actuarial Process	Databricks-Enabled Process
Data Storage	Separate databases, manual handling	Centralized cloud-based data lakes
Processing Speed	Slow, batch processing	Fast, real-time analytics
Collaboration	Limited data sharing	Seamless collaboration across teams
Risk Modeling	Manual, time-consuming	Automated, AI-driven insights
Regulatory Compliance	Complex, error-prone	Streamlined with automated tracking

Table 2: Traditional Actuarial Processes vs. Databricks-Enabled Processes

4. LEVERAGING ADVANCED ANALYTICS FOR ACTUARIAL PREDICTIVE MODELING

4.1 Enhancing Risk Assessment with Machine Learning

Actuarial predictive modeling has grown better through machine learning integration which gives valuable tools for risk evaluation. Supervised learning methods help underwriters classify the level of insurance risk by examining similar models of decision trees, logistic regression, and support vector machines. The system delivers forecasts about future claims chances by examining past information of risk components. Supervised learning helps insurance companies better select policy risks and organize clients by danger level to price policies more effectively and lower their company's potential losses (Li et al., 2017).

Because of its unique capability, unsupervised learning is needed to find abnormal patterns in claims data. Our analysis uses PCA and clustering algorithms to spot behavior in insurance claims that differentiates from normal activities of honest clients. The discovery of unusual claims helps insurers start early investigations to stop fraudulent activity from creating financial hardship (Achieng, 2017). K-means and DBSCAN algorithms effectively divide claims data into risk pools by finding irregular patterns in claim records.

Databricks offers strong tools for auto insurance risk division by processing large claims and customer records with machine learning to give precise risk forecasts. Insurers try better segments with Databricks data analytics tools to study users better and determine rates correctly (Vernik et al., 2017). Such live risk pooling insights help insurers study customer groups to adjust their underwriting standards.

4.2 Improving Claims Forecasting and Reserving Models

The prediction of future claims and allocation of financial safety funds form the essential tasks that actuarial professionals handle. Trusted actuarial methods depend on historical numbers while company development requires machine learning algorithms especially ARIMA systems and Long Short-Term Memory networks to boost forecasting output. These systems process historical claims records to generate better estimates for future reserves (Xu & Xu, 2018).

ARIMA suits linear time series data because it performs well with structured patterns yet LSTMs process non-linear patterns since they are built on recurrent neural networks. The long-term trending and sequential pattern detection of LSTMs make them perfect for creating future claims outcomes based on past data patterns as stated by Raghavendra and Bheemanagouda in 2019. The improved forecasting methods of modern computers outperform regular techniques at predicting how much money will be needed for future claims.

Advances in technology help both companies analyze and stop fraudulent activity at the moment it happens. Insurers enhance their claim prediction system by using Databricks technology to evaluate fresh information straightaway. These advanced models respond immediately to updates in circumstances which boosts their ability to estimate claims correctly (Sawadogo & Darmont, 2021). Through Databricks the company tracks claims trends better using customer actions alongside historical claims and outside data. When insurers review this information they can avoid financial loss and stay secure by changing their funds available for payments (Eder & Shekhovtsov, 2021).

4.3 Dynamic Pricing and Policy Personalization

The new actuarial models force companies to adjust their pricing practices by using instant data analysis. Insurers are developing custom price plans based on how risky each customer acts. Machine learning algorithms analyze entire databases of data about each policyholder to create pricing plans that show exactly how much risk each customer represents (Che & Duan, 2020). Auto insurance businesses use telematics to monitor driving patterns in real-time for making immediate updates to premium rates when drivers experience safe or unsafe practices. The system gathers vehicle data from IoT devices which then moves to a database for machine learning analysis and price changes happen instantly.

Using behaviour data has become a key method for life insurance companies to set their price models. Atopyimation depends on studying how policyholders move physically as well seeing their fitness results and life habits. Insurance companies can craft better prices for each customer according to their specific risk profile while maintaining great profitability success (Eichler et al., 2021).

4.4 Automating Actuarial Workflows with AI and Big Data

AI and big data technology improve existing actuarial tasks by means of automation. Most actuarial processes including analyzing data and setting reserves depend on extensive human-based labor which raises potential for human mistakes. Databricks AutoML tools enable actuaries to streamline routine work so they can use their time more effectively for important business planning decisions. AutoML frameworks let actuaries build and test predictive models quickly since they eliminate the need for programming knowledge (Bariff, 2019).

The use of AI technology enhances both scenario testing and stress testing methods to speed up actuarial work processes. Manual updates by actuaries were essential for scenario analysis but AI helps them test many models faster across diverse market events. AI and big data technology enables actuaries to conduct faster scenario simulations that help them develop correct forecasts about how market changes will impact their portfolio portfolios (Shirke et al., 2017). Numerical systems enable better risk decisions that protect insurers' operational stability.

Advanced analytics tools help actuarial science organizations improve their processes of risk evaluation while enhancing claim forecast accuracy and pricing strategies plus automating work procedures. Machine learning tools help insurance companies separate risks precisely and find fraudulent activities better through supervised and unsupervised methods while time series predictors enhance their ability to project claims and set appropriate financial accounts. Real-time processing of data and human behavior tracking helps insurers set better custom prices while Databricks AutoML tools make actuarial work easier and faster and lower error rates. Insurers will experience better operational performance as machine learning advances further into their business operations (Li et al., 2017; Xu & Xu, 2018).

5. IMPLEMENTATION STRATEGIES FOR ACTUARIAL TEAMS

5.1 Migrating from Legacy Systems to Databricks

5.1.1 Step-by-Step Guide for Integrating Databricks into Actuarial Workflows

Switching from old actuarial platforms to Databricks needs a defined method to work properly. The key steps include:

- Teams should examine their present actuarial workflows to find how data processing takes too long and storage space limits them (Databricks, 2017).
- Data Migration Strategy: Utilize Apache Spark and Stocator for high-performance data transfer from legacy databases to cloud-based environments (Vernik et al., 2017).
- We develop ETL processes to automate the extraction of data then normalize and filter it before moving it to Databricks platform (Shirke et al., 2017).
- Databricks parallelization lets us adjust actuarial models to increase their predictive quality according to Achieng (2017).
- A full test phase will show if the actuarial formulas work without issues after the database move (Xu & Xu, 2018).
- Train actuarial professionals to properly use Databricks functions through a structured program (Li et al., 2017).

5.1.2 Challenges and Best Practices in Transitioning from On-Premises Systems

Moving actuarial systems from earlier methods to Databricks proves hard because companies face data_restrictions, inspection demands and employee training needs. Best ways to handle these difficulties are listed below:

- Migrate the actuarial system in small steps instead of one big transformation to keep normal operations running (Sawadogo & Darmont, 2021).
- Databricks user's access rights and policyholder data encryption should be deployed for secure digital asset protection (Eder & Shekhovtsov, 2021).
- Auto-scaling in Databricks lets you adjust resources for optimal cost management as described by Elragal and Hassanien in their research 2019.

5.2 Optimizing Data Lakes for Actuarial Data Management

5.2.1 Specifying Actuarial Database Design to Enhance Retrieval Speed

Actuarial data management needs properly organized data lakes. Key structuring principles include:

- Adopt schema-on-read that responds smoothly to actuarial data format updates as explained in Che & Duan's research (2020).
- The actuarial strategy of dividing databases depends on policy types and risk groups to help users locate needed data faster (Belov et al., 2021).
- The system tracks actuarial data sources using metadata models to maintain its validity (as per Eichler et al. 2021).

5.2.2 Using Delta Lake improves data history tracking and security supervision

With Delta Lake users can work with data lakes in new ways that include:

- ACID Transactions: Ensuring consistency in actuarial computations across large-scale datasets (Richards, 2017).
- We can determine actuarial model changes and access prior dataset versions to support compliance reporting through Delta Lake's time travel feature as described in Patwardhan et al. (2019).
- The system automatically removes unused actuarial records to keep storage space at its peak quality (Sumasgutner et al., 2019).

5.3 Training Actuarial Teams in Cloud-Based Data Science

5.3.1 Importance of Upskilling Actuaries in Python, Spark, and Databricks Notebooks

Actuarial experts who work with data need to develop their knowledge of Python Databricks and Apache Spark for success in data-driven fields. Benefits include:

- Machine learning tools help actuaries make better risk assessments according to scientific research (Tang et al., 2018).
- Single View for Open-source Tools: Spark supports big actuarial data handling at scale by Križanović et al. (2018).
- Actuaries can test new model scenarios within the Databricks Notebook environment live (Hengl et al., 2018).

5.3.2 Recommended Resources and Certifications for Actuarial Data Science

Actuaries should focus their learning path on obtaining these resources to improve their skills.

- Databricks Certification: Courses such as "Data Engineer Associate" and "Machine Learning Specialist".
- Students can find online Python training to learn how insurance analytics uses NumPy and SciPy with Pandas features.
- Our program includes both PySpark and distributed computing framework education modules.

5.4 Ensuring Regulatory Compliance and Data Security

5.4.1 The security capabilities of Databricks help us properly manage our policyholder data

Actuarial firms need to make secure data protection their top priority for policyholder information defense. Key security features include:

- Data encryption both when it sits idle and while being transmitted helps protect information from breaches according to Nicol et al. (2019).

iJETRM

International Journal of Engineering Technology Research & Management

Published By:

<https://www.ijetrm.com/>

- Identity and Access Management (IAM) system protects user access to data by enforcing secure login procedures (as explained by Fuller, 2019).
- Audit Logging: Tracking all data modifications for transparency and regulatory compliance (Benuzillo et al., 2019).

5.4.2 Meeting Actuarial Industry Regulations (GDPR, Solvency II, IFRS 17)

Actuarial data management needs to follow global rules and regulations of the actuarial industry.

- General Data Protection Regulation (GDPR): Ensuring consent-based data processing and the right to erasure for policyholders (Eder & Shekhovtsov, 2021).
- The organization needs to keep regulatory approved actuarial risk models ready for Solvency II examination (Bariff, 2019).
- The Cosma et al. paper (2017) explains how standardized actuarial accounting under IFRS 17 helps companies share transparent financial numbers.

Companies can modernize their business practices and limit risk exposure by bringing actuarial systems and data lakes into Databricks plus offering actuarial staff training plus keeping all rules.

6. FUTURE TRENDS IN ACTUARIAL SCIENCE WITH DATABRICKS

6.1 Expansion of AI-Driven Actuarial Modeling

Technical advancements with deep learning now speed up actuarial science research especially when used for mortality and morbidity risk evaluation according to Raghavendra and Bheemanagouda (2019). Machine learning technology helps insurers make better price estimates so they can manage their customer groups more effectively. XAI technology is necessary because XAI helps actuarial companies meet regulatory requirements and understand their risk models better (Xu & Xu, 2018). When authorities need AI actuarial insights they must follow XAI systems for better risk management and rate setting.

6.2 Real-Time Data Integration with IoT and Wearables

The use of Internet of Things devices and wearables helps insurance models work with live health and behavioral information. Through smartwatches and fitness trackers insured individuals can develop tailored health and life insurance rates because their biometric information is constantly updated (Achieng, 2017). IoT technology helps cars share driving information in real-time to evaluate insurance risk levels which supports usage-based premium changes (Li et al., 2017). Streaming data needs advanced data lake and distributed computing tools from Databricks to work with efficiently as per Sawadogo and Darmont (2021). Security needs must include effective encryption methods and agreed rules to protect private information.

6.3 Decentralized and Blockchain-Based Actuarial Data Management

Blockchain technology will change actuarial science by setting up protected systems to store data across several computers without a central point of access. By using smart contracts insurers can modernize their operations along with providing better policy formation while catching fraudulent actions automatically. This technology saves administrative resources while improving customer trust (Li et al., 2017). DeFi systems allow people to create insurance arrangements outside traditional insurance companies and reduce dependence on established risk carriers according to Vernik et al. (2017). These new technologies benefit insurance operations but face issues when standards organizations accept them and when they need to work with existing actuarial systems as outlined by Eichler et al. in 2021.

Over time the actuarial business needs AI and real-time data analytics skills as well as blockchain use for competitive success. The scalable AI-driven analytics platform of Databricks helps actuaries use these developments effectively for data-based fast decision-making in insurance businesses.

7. CONCLUSION

Actuarial science now has a breakthrough because the combination of Databricks data lakes and advanced analytics works successfully. These technologies simplify information processing and can better forecast trends while giving users more correct decisions. Databricks offers powerful and expandable technology that lets actuaries handle big data at speed (Databricks, 2017). Data lakes give companies flexible storage that handles structured and unstructured data

IJETRM

International Journal of Engineering Technology Research & Management

Published By:

<https://www.ijetrm.com/>

which enables live analysis and better risk evaluation according to Sawadogo and Darmont (2021). Advanced analytics helps actuaries make better predictions and improve their actuarial modelling process by using tools described in Patwardhan et al. (2019).

Actuarial firms that want to succeed need to adopt these data-based ways of working today. The practice of real-time large data analysis has become mandatory for modern business operations. Firms can improve their risk models while better pricing products and fighting fraud by processing data lake information through cutting-edge analytics tools (Eichler et al., 2021). Databricks implementation helps multiple teams work together while automating their processes which saves money according to Vernik et al. (2017).

The actuarial science field predicts that future modelling will lead to successful growth opportunities. Actuarial experts will understand risks and customer movements better through AI improvements so they can make greater predictions (Tang et al., 2018). To succeed in this field companies need robust data governance systems that accurately handle and properly use business information as Eder and Shekhovtsov (2021) explain. The actuarial profession enhances its analysis and reaches better business results by using emerging technology.

The moment has arrived for actuarial firms to start using advanced ways of analysis as they strive to lead their market.

REFERENCES

- [1] Achieng, O. M. (2017). Actuarial Modeling for Insurance Claim Severity in Motor Comprehensive Policy Using Industrial Statistical Distributions. International Congress of Actuaries, 1–29.
- [2] Bariff, M. L. (2019). Advanced analytics group and intraorganisational power. International Journal of Technology Management, 79(2), 108–125. <https://doi.org/10.1504/IJTM.2019.097521>
- [3] Belov, V., Kosenkov, A. N., & Nikulchev, E. (2021). Experimental characteristics study of data storage formats for data marts development within data lakes. Applied Sciences (Switzerland), 11(18). <https://doi.org/10.3390/app11188651>
- [4] Benuzillo, J., Savitz, L. A., & Evans, S. (2019). Improving Health Care with Advanced Analytics: Practical Considerations. EGEMs (Generating Evidence & Methods to Improve Patient Outcomes), 7(1), 3. <https://doi.org/10.5334/egems.276>
- [5] Che, H., & Duan, Y. (2020). On the Logical Design of a Prototypical Data Lake System for Biological Resources. Frontiers in Bioengineering and Biotechnology, 8. <https://doi.org/10.3389/fbioe.2020.553904>
- [6] Cosma, G., Brown, D., Archer, M., Khan, M., & Graham Pockley, A. (2017, March 15). A survey on computational intelligence approaches for predictive modeling in prostate cancer. Expert Systems with Applications. Elsevier Ltd. <https://doi.org/10.1016/j.eswa.2016.11.006>
- [7] Databricks. (2017). The Data Scientist's Guide to Apache Spark. Databricks, 1–103.
- [8] Eder, J., & Shekhovtsov, V. A. (2021). Data quality for federated medical data lakes. International Journal of Web Information Systems, 17(5), 407–426. <https://doi.org/10.1108/IJWIS-03-2021-0026>
- [9] Eichler, R., Giebler, C., Gröger, C., Schwarz, H., & Mitschang, B. (2021). Modeling metadata in data lakes—A generic model. Data and Knowledge Engineering, 136. <https://doi.org/10.1016/j.datak.2021.101931>
- [10] Elragal, A., & Hassanien, H. E. D. (2019). Augmenting advanced analytics into enterprise systems: A focus on post-implementation activities. Systems, 7(2). <https://doi.org/10.3390/systems7020031>
- [11] Fuller, S. (2019). Leveraging Governance to Derive Value from Advanced Analytics. North Carolina Medical Journal, 80(4), 237–239. <https://doi.org/10.18043/ncm.80.4.237>
- [12] Hengl, T., Nussbaum, M., Wright, M. N., Heuvelink, G. B. M., & Gräler, B. (2018). Random forest as a generic framework for predictive modeling of spatial and spatio-temporal variables. PeerJ, 2018(8). <https://doi.org/10.7717/peerj.5518>
- [13] Križanović, V., Žagar, D., Grgić, K., & Vranješ, M. (2018). Enhanced predictive modelling process of broadband services adoption based on time series data. Advanced Engineering Informatics, 38, 142–167. <https://doi.org/10.1016/j.aei.2018.06.003>
- [14] Li, S., Yin, C., Zhao, X., & Dai, H. (2017). Stochastic Interest Model Based on Compound Poisson Process and Applications in Actuarial Science. Mathematical Problems in Engineering, 2017. <https://doi.org/10.1155/2017/3472319>

IJETRM

International Journal of Engineering Technology Research & Management

Published By:

<https://www.ijetrm.com/>

- [15] Nicol, E. D., Norgaard, B. L., Blanke, P., Ahmadi, A., Weir-McCall, J., Horvat, P. M., ... Leipsic, J. (2019, June 1). The Future of Cardiovascular Computed Tomography: Advanced Analytics and Clinical Insights. JACC: Cardiovascular Imaging. Elsevier Inc. <https://doi.org/10.1016/j.jcmg.2018.11.037>
- [16] Patwardhan, R. S., Hamadah, H. A., Patel, K. M., Hafiz, R. H., & Al-Gwaiz, M. M. (2019). Applications of Advanced Analytics at Saudi Aramco: A Practitioners' Perspective. Industrial and Engineering Chemistry Research, 58(26), 11338–11351. <https://doi.org/10.1021/acs.iecr.8b06205>
- [17] Raghavendra, K. S., & Bheemanagouda. (2019). Study on actuarial science and actuaries-the pioneer of insurance. International Journal of Advanced Science and Technology, 28(20), 1266–1281.
- [18] Richards, D. (2017). Responsible retail: treating customer data with care. InfoWorld.Com.
- [19] Sawadogo, P., & Darmont, J. (2021). On data lake architectures and metadata management. Journal of Intelligent Information Systems, 56(1), 97–120. <https://doi.org/10.1007/s10844-020-00608->
- [20] Shirke, S. A., Gosavi, T., Mishra, A. K., Singh, V. V., & Srivastava, A. (2017). Performance enhancement of apache APEX. In Proceedings of the International Conference on Electronics, Communication and Aerospace Technology, ICECA 2017 (Vol. 2017-January, pp. 660–663). Institute of Electrical and Electronics Engineers Inc. <https://doi.org/10.1109/ICECA.2017.8203621>
- [21] Sumasgutner, P., Koeslag, A., & Amar, A. (2019). Senescence in the city: exploring ageing patterns of a long-lived raptor across an urban gradient. Journal of Avian Biology, 50(12). <https://doi.org/10.1111/jav.02247>
- [22] Tang, F., Xiao, C., Wang, F., & Zhou, J. (2018). Predictive modeling in urgent care: A comparative study of machine learning approaches. JAMIA Open, 1(1), 87–98. <https://doi.org/10.1093/jamiaopen/ooy011>
- [23] Vernik, G., Factor, M., Kolodner, E. K., Ofer, E., Michiardi, P., & Pace, F. (2017). Stocator: A high performance object store connector for spark. In SYSTOR 2017 - Proceedings of the 10th ACM International Systems and Storage Conference. Association for Computing Machinery, Inc. <https://doi.org/10.1145/3078468.3078496>
- [24] Xu, C. cong, & Xu, Z. liang. (2018). An Actuarial Approach to Reload Option Valuation for a Non-tradable Risk Assets under Jump-diffusion Process and Stochastic Interest Rate. Acta Mathematicae Applicatae Sinica, 34(3), 451–468. <https://doi.org/10.1007/s10255-018-0759-5>