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AI-Driven Incident Prediction Models for Proactive IT Operations Management

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ABSTRACT: The combination of AI and Big Data has opened many valuable opportunities for the digital enterprise across various business segments. One area that lacks sufficient attention, especially from the AI community, is proactive (event) management of enterprises' IT operations. Proactive IT operation management constitutes one of the future trends of IT services, with the promise of lowering the cost of service outages and failures. Most organizations still perform IT operations in a passive manner, implementing preventive measures and performing incident and problem management instead of predicting service outages in advance. As a result, despite their demand and potential, such tools are usually not part of the operational toolbox of most organizations.

Building on the available data streams, novel ML models and tools can be designed to predict failures in enterprise IT environments, service outages and IT service degradation. The information produced can be fully exploited in the context of enterprise monitoring, capacity management and business continuity management, and the generated alerts can assist incident management teams. These solutions assist organizations in moving toward a more proactive IT operations management strategy. The models can also serve other areas apart from predictive incident management. In any use case where a time series has to be closely monitored and where sudden changes can have a large impact, the proposed approach can be used. Use cases include real-time alerting and thresholding, predictive capacity planning and budget forecasting.

KEYWORDS: Service operation management; IT Systems Management; predictive analytics; time series forecasting; anomaly detection; SRE; ITSM; artificial intelligence; machine learning; supervised learning; unsupervised learning; data science; data-driven decision making; correlation analysis; classification; capacity management; performance management; monitoring; resource provisioning; budgets; resource usage; incident management; IT incidents.

I. INTRODUCTION

Both the growing complexity of IT installations and the mission-critical nature of IT services demand an increasing proportion of IT expenditures be devoted to operations and support, particularly in large enterprise environments. Proactive IT operations management, in the context of predictive maintenance, has been an active area of research. Machine learning models have the capacity to predict errors, faults, and performance anomalies. A large enterprise with a diverse set of business functions and user bases can be thought of as a set of independently operated products. Users of any product experience a high rate of service incidents when the product is undergoing an abnormal condition.

This work leverages the conclusions of machine learning research. An IT infrastructure of more than a hundred system components is modeled as combination of multiple machine-learning classification models that predict incident series. Each individual machine-learning classification model predicts the incident boundary condition for one incident type of one product with a temporally lagged configuration. The output of these models is an IT operations alerting system advised by temporally ordered lags, thresholds, historical events, and duty rotations. Alerts issued by machine-learning models are predictable user incidents. Enhanced machine-learning models—trained as such—achieve a higher mutual information score with the original user incident time series than the baseline user incident time series.

1.1. Background and Significance

IT Operations-on the management of information technology resources and services that support the delivery of business processes and services-are necessary but still often functionally and/or organizationally siloed. Nevertheless, the increasing interdependence and scale of those resources requires a more unified approach to their end-to-end management. This necessity is compounded by growing business demand which not only stresses service reliability but also increases resource and infrastructure provisioning costs. The research described herein addresses both problems

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through a set of AI-driven models for predicting the flow of incidents and faults, hence providing enhanced situational awareness and enabling proactive capacity management.

Service-reliability and -availability problems stem from faults in the underlying hardware, software and network resources. An efficient way of improving a service's reliability is to develop a predictive model that forecasts future service incidents. Today's enterprise cloud infrastructures are equipped with dedicated monitoring systems that generate large amounts of time series for service-level indicators (SLIs). Such indicators provide useful information for future incident prediction tasks, as shown. Various time series forecast models are combined with incident event history data to create data-deficient yet highly automated models. These models generate near real-time alerts on expected incident volumes for different windows of the next 72 hours, with the aim of informing related incident-management processes.

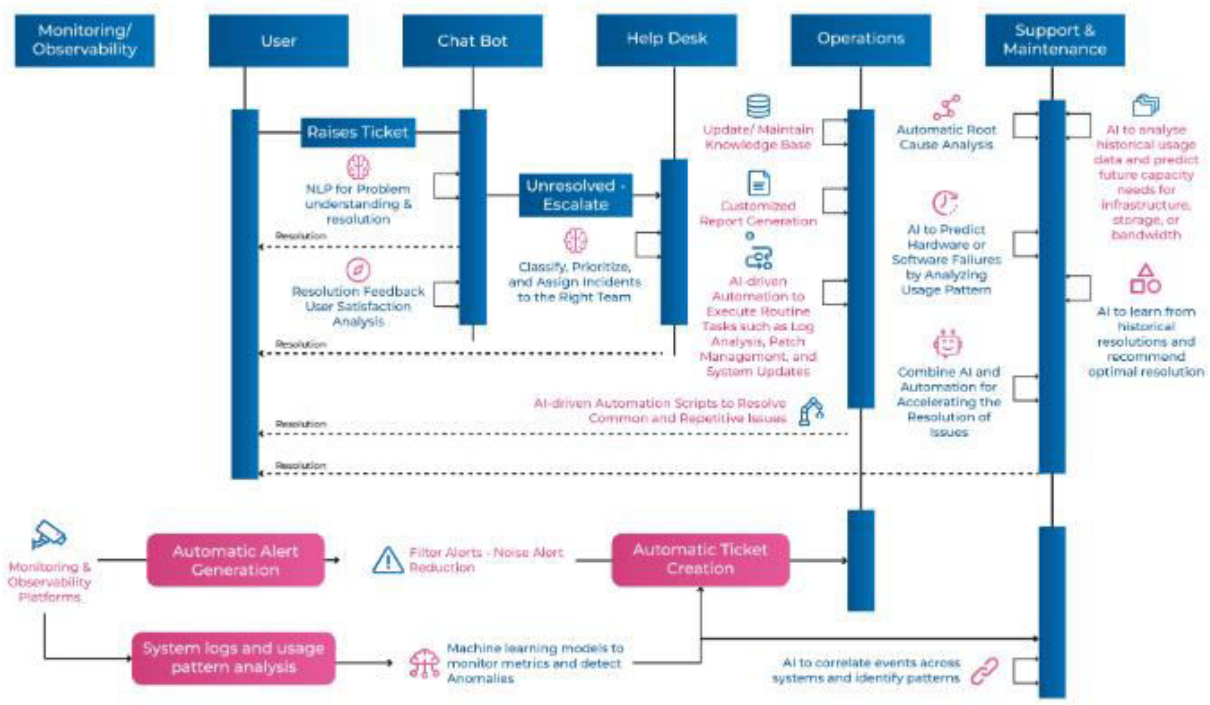

Fig 1: AI in Incident Management

1.2. Research design

Pragmatic Design Science Research PDSR is applied to develop incident prediction models in an artificial intelligence systems development context that support pragmatic Theory Construction TC objectives. PDSR is characterised by an iterative sequence of modelling steps akin to those of conventional design science research, but with the specification of each model guided by a tentatively formulated Theory and a brief, relatively-Aryan model specification. Such specified models are then empirically tested but without a corresponding explicit, formal Theory of their own. The specificities and mechanisms of several common AI models determine their behaviour, but those do not constitute a Theory of AI models. Each model behaviour is simply evaluated to assess behaviour quality. Evaluation may then reveal a model's support for a TC problem-situation, a test case setup for another model, or novelty needed for that situation.

Equation 1: Logistic model (standard operational choice)

A common operational model for probability is logistic regression:

$$p_t = \sigma(z_t), z_t = w^\top X_t + b, \sigma(z) = \frac{1}{1+e^{-z}}$$

Step-by-step derivation of the sigmoid form from log-odds

1. Define odds:

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$$\text{odds}_t = \frac{p_t}{1 - p_t}$$

2. Define log-odds (logit) as linear in features:

$$\log\left(\frac{p_t}{1 - p_t}\right) = w^\top X_t + b$$

3. Exponentiate:

$$\frac{p_t}{1 - p_t} = e^{w^\top X_t + b}$$

4. Solve for p_t:

$$p_t = (1 - p_t)e^{w^\top X_t + b}$$
$$p_t + p_t e^{w^\top X_t + b} = e^{w^\top X_t + b}$$
$$p_t(1 + e^{w^\top X_t + b}) = e^{w^\top X_t + b}$$
$$p_t = \frac{e^{w^\top X_t + b}}{1 + e^{w^\top X_t + b}} = \frac{1}{1 + e^{-(w^\top X_t + b)}}$$

II. BACKGROUND AND MOTIVATION

Data-driven Proactive IT Operations Management in the Modern Enterprise
In recent years, enterprises have turned information technology (IT) capabilities into competitive advantages. Owing to the critical role IT plays in supporting the core business of an enterprise, enormous investments have emerged for building reliable IT services. Faults and incidents are thus of great concern for enterprise IT service providers. More importantly, being aware of incidents (especially large-impact incidents) in advance provides a clear window for improving IT service reliability. Proactive IT operations management is enabled by sensing events through data-driven incident prediction models. Enterprise applications, such as real-time IT incident alerting and predictive capacity planning, follow the line of IT incident prediction.

Proactive IT operations management (PITOM) aims to provide useful warnings for potential incidents to the IT service provider. Recently, prediction or forecasting capabilities have gained momentum in previous literature, enhancing standard monitoring/alerting processes and promoting novel fields, such as predictive capacity planning. Consequently, it is beneficial to build a data-driven process to monitor system behaviors and detect anomalies, toward the goal of predicting incidents. Incidents or problems may occur when an operational parameter exceeds its alerting threshold or when an operational attribute, or a metric generally viewed from the business perspective, approaches an incident threshold. Alerts from the standard monitoring system can represent a useful signal for the underlying service's health. For instance, ongoing procurement can be initiated when pending requests in an IT service queue exceed a certain threshold.

2.1. IT Operations Management in the Modern Enterprise

Analysis of organizational operations during the last years identified three key drivers. First, companies' business environments remain volatile and uncertain. Second, businesses in all sectors have become highly reliant on technology. Therefore, successful IT operations management continues to grow in significance as organizations increasingly depend on IT services to automate and support business processes. Being a critically differentiated technology function that enables an organization's IT environment to run consistently and securely, IT operations management is charged with sustaining and improving service operations and reliability.

During the life cycle of an application or service, incidents and operations faults can occur, affecting the correct functionality. Consequently, faults and incidents are considered the most common activities impacting service reliability. Examining historical operational data can yield insights into the occurrence of incidents, help IT operations managers understand the reasons behind these incidents, and equip them with the necessary information to reduce the likelihood of incidents in the future. For such a purpose, predictive models are suitable because they can inform operational teams and operations specialists when a future incident is expected or likely, allowing for proactive remediation.

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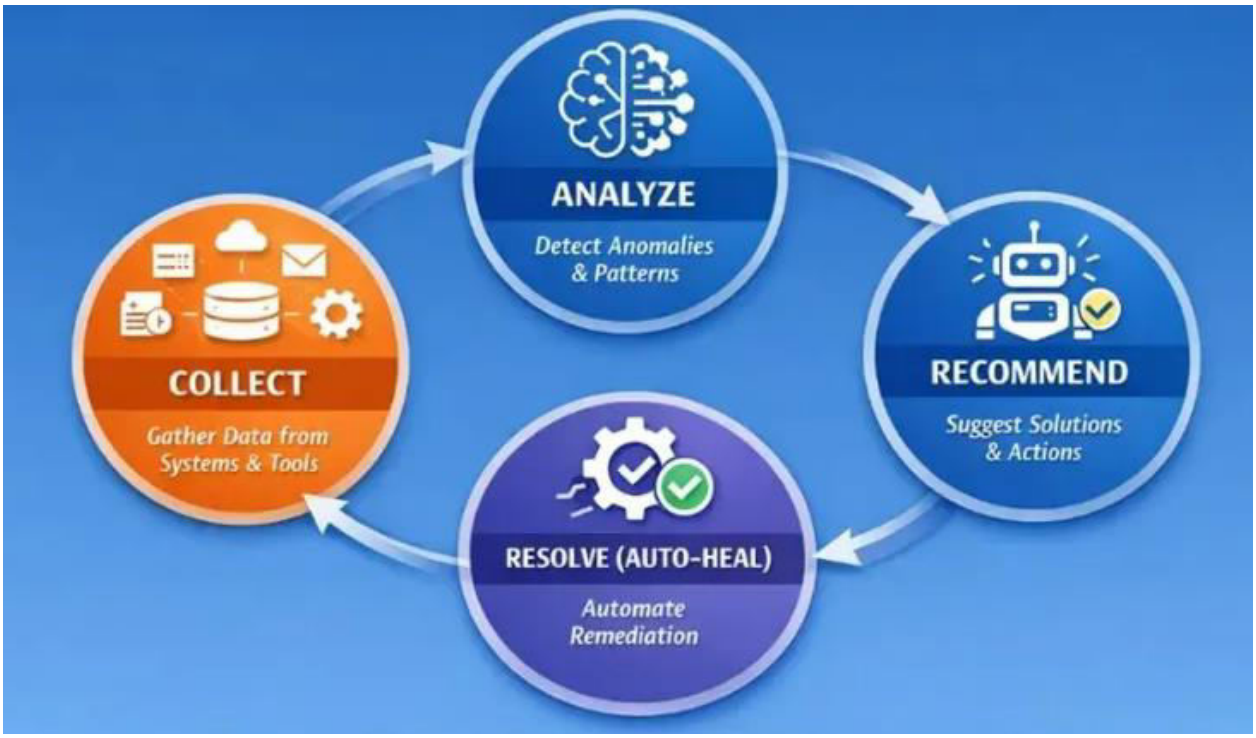

Fig 2: Enterprise AI Ops (AIOps) model transforming IT operations

2.2. Faults, Incidents, and Service Reliability

A standard model of incident response includes three stages: detection, diagnosis, and resolution. Detection means sensing an incident and raising an alert. Diagnosis is a process of determining the root cause, typically using a combination of human effort and automated diagnostic tools. Finally, resolution consists of rectifying the root cause within the system. Because resolution normally requires human effort, the time taken to resolve an incident is usually much higher than the time taken to detect it. The standard model assumes that fault detection is 100% accurate and that detected faults are always diagnosed and resolved. In reality, this is rarely the case. Detecting faults usually introduces false positives—alerts that signal a fault when there is none—and false negatives—situations in which a fault is present but is not detected. The accuracy of the entire process hinges on the fault detection and diagnosis. Nonetheless, the fundamental principle remains: the sooner a fault is detected, the sooner action can be taken to remediate it.

In IT operations, the most critical faults are those that propagate and cause incidents, which are interruptions or degradations of service that affect customers. The moment a fault propagates, it can be considered an incident. This makes incident detection highly reliable and minimizes the need for diagnosis. What is required instead is a mechanism that predicts the probability of an incident occurring in the future, that is, whether or not an incident will happen in the next 1, 5, or 30 minutes. Such predictions enable proactive rerouting of traffic and other timely measures to reduce service downtime and degradation. Traffic pattern changes and capacity saturation can also be included as prediction targets.

Equation 2: Incident volume as a count time series + forecasting thresholds

Let $y_t \in \{0,1,2, \dots\}$ be incident count in time bucket t(hour/day).

Given history $y_{t-L+1}, \dots, y_t$, predict next Hsteps:

$$\hat{y}_{t+1}, \dots, \hat{y}_{t+H}$$

i.e.

$$\hat{\mathbf{y}}_{t+1:t+H} = f_\theta(y_{t-L+1:t}, X_{t-L+1:t})$$

The operational thresholding described in the paper is commonly implemented as:

$$U_{t+h} = \hat{y}_{t+h} + k \cdot \hat{\sigma}_{t+h}, L_{t+h} = \max\{0, \hat{y}_{t+h} - k \cdot \hat{\sigma}_{t+h}\}$$

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Then:

High-volume alert if $y_{t+h} > U_{t+h}$
Low-volume / drop alert if $y_{t+h} < L_{t+h}$

III. PROBLEM FORMULATION

Prediction models of information technology (IT) service incidents are constructed based on three distinct types of prediction targets: incident volume, incident counts classified by category, and incident rate. The broadest prediction target is the predicted volume of IT service incidents. Such models are essential for real-time alerting during the operation of IT services, predictive capacity planning, and proactive management of IT services. Two metrics are defined for model evaluation, taking into account real production operations.

3.1. Definitions and Scope
The process of information technology service management (ITSM) involves monitoring and managing IT service operations to sustain IT service quality. It encompasses the detection, reporting, investigation, diagnosis, and restoring of incidents, which are unplanned problems causing service disruptions. Incidents must be resolved within agreed service levels to maintain the quality of IT services. Failure to meet service levels for high incident volumes, incident counts for individual types, or incident rates can lead to service-level agreement (SLA) violations. Prediction models for each of these elements help avert SLA violations by alerting stakeholders in advance. Models are advanced by predicting the volume of IT service incidents over a forecasting horizon, classifying incident counts into categories, and predicting incident rate growth.

Incident volumes follow a count process, making prediction challenging. The target variable is provided by incident management systems, and discharge time-series data is processed to satisfy established time-series forecasting conditions. The neural network-based Long Short-Term Memory (LSTM) algorithm is used to predict incident volumes over various forecasting horizons, and actual values are compared against predicted upper and lower thresholds. Fine-grained incidents are also predicted using both classification models and Multi-Class Classification (MCC)-based methods. Finally, incident rates are predicted because these growth rates require extremely low-control limits to be formed in production sets.

3.1. Definitions and Scope
A fault is defined as an abnormal condition of a component that may cause an interruption of the service; an incident is defined as an unplanned interruption or a reduction in the quality of a service. The impact incurred by a fault continues to evolve over time before there is actually a service failure. Reducing the time between detection of an incident and its remediation is generally not a cost-saving measure, as urgency drives increased costs. Nevertheless, nevertheless efficiently managing the incident-handling process can minimize, but not eliminate, the total cost incurred by a given number of incidents. Often it is much more efficient to perform corrective actions before the incident materializes Service reliability is mainly defined in terms of the frequency and duration of incidents. IT operations management must thereafter concentrate on these metrics. Thus AI-driven models that predict the occurrence of incidents are of interest. The term predictive analytics is often used to define situations in which machine learning techniques are applied to historical data so as to detect patterns and/or identify trends and relationships that could improve the accuracy of predictions.

For the purpose of developing predictive models, the label associated with an individual time-series segment need to indicate whether an incident occurred in some future window, usually salient to operations and the business. The label can therefore be constructed from the historical incident logs if the data is adequately enriched via feature engineering. Feature engineering for predictive models in this domain is characterized by the use of multi-source time-series data. The presence in the logs of multiple external factors, such as those describing the load on the systems or the status of the IT support, enables useful labels to be generated to augment the internal data of the IT organization, such as events, alarms and monitoring status.

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Equation 3: ARIMA family equations (the classical baseline the paper references)
Define the backshift operator $By_t = y_{t-1}$.
ARMA(p,q):

$$y_t = c + \sum_{i=1}^{p} \phi_i \, y_{t-i} + \varepsilon_t + \sum_{j=1}^{q} \theta_j \, \varepsilon_{t-j}$$

where $\varepsilon_t$is white noise.

3.2 Add integration: ARIMA(p,d,q)
If non-stationary, difference $d$times:

$$\nabla y_t = y_t - y_{t-1}, \nabla^d y_t = (1-B)^d y_t$$

ARIMA(p,d,q) is ARMA(p,q) applied to $\nabla^d y_t$:

$$\phi(B)(1-B)^d y_t = c + \theta(B)\varepsilon_t$$

with:

$$\phi(B) = 1 - \phi_1 B - \cdots - \phi_p B^p, \theta(B) = 1 + \theta_1 B + \cdots + \theta_q B^q$$

3.2. Prediction Targets and Metrics
Three categories of operational data correlate with failure incidents for non-production infrastructures: monitored alarms, traffic metrics, and availability metrics. The target for supervised models is the debut of incident tickets in a forecast window, bolstered by time-to-fail indicators. Other prediction tasks include forecasting traffic loads, anomaly detection, and real-time alerting of non-recurrent service behaviour.

Time series data from cloud platforms and traffic routers support a combined model. Clouds provider infrastructure services to virtual machines; virtual machines and routing services together host application layer services. All dependencies are recorded and used to build a directed graph that links predictions across layers. The aim is to provide proactive support opportunities for every IT service.

Time series models, supervised machine learning classifiers, unsupervised statistical tests, and thresholding Detector settings - modelling false positives and real positives can be kept under control, with the trade-off depending on the operational context and the application.

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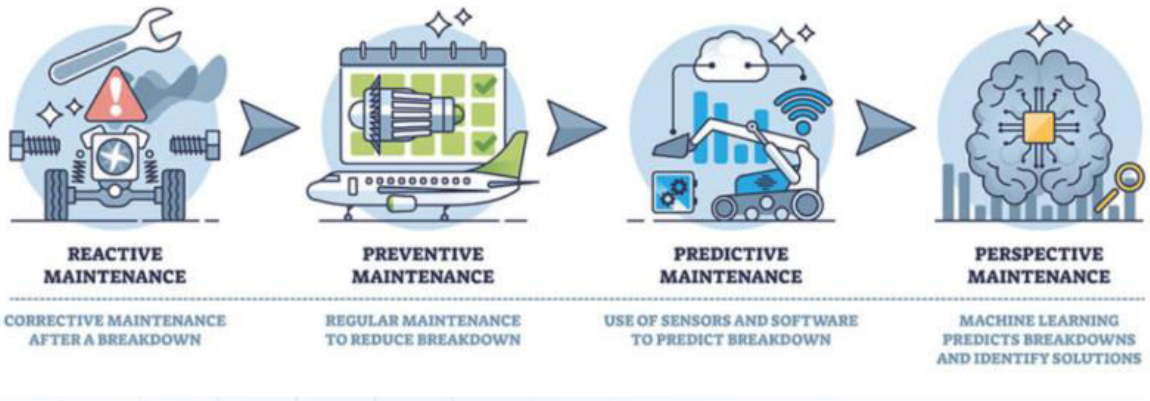

Fig 3: AI-Powered Predictive Maintenance

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IV. METHODOLOGICAL FOUNDATIONS

Understanding the empirical challenges of incident prediction requires a methodological foundation that connects data collection and preprocessing to the design of predictive models and associated evaluation vehicles. The first step in the phase of operationalization is to create virtual labels reflecting the presence of incidents for an analysis horizon, typically the next seven days, on the basis of historical data for faults and service incidents. Individual records are marked in this way for the closest subsequent incident per IT service that was created more than 10 minutes after the actual record date and also for the next following incidents that were created within 48 hours of the original record date. Similar labels are generated for fault statements. Features are derived from attributes contained in the available data set, paying special attention to the selection of those features yielding the highest predictive performance.

An additional aspect of predictive modeling for faults and incidents, which has still not been investigated sufficiently, concerns the methodology for quantifying the predictive power. While conventional prediction metrics based on the confusion matrix are indeed useful, they consider predictive capability only in a small time frame around the label and demand a minimum number of predictions on a specific date to be meaningful. A promising alternative is to disregard the time dimension altogether and adopt a different modeling approach that retains as much information as possible about the forecasted label while discarding the precise prediction date of the labels and just keeping the time in which those labels appear.

4.1. Data Collection and Preprocessing

The required historical IT Operation Management (ITOM) data is sourced from enterprise-grade ticketing systems that operate across a geographically distributed cloud infrastructure. The datasets consist of production-support-related incidents, such as performance and service degradation issues, and faults related to user experience and application issues. Incidents predominantly arise from monitored IT components, while unmonitored resources cause faults. Incidents and faults formed two classified outputs for supervised predictive demand models. The accurate working status of all IT components connected through telemetry and monitoring and the availability of all associated correlating features are essential for AI-driven demand prediction. Engineered features include past incident/fault intensity, time series data of clouds and their application components, and alphabetical seasonality encoded across both the incident and fault datasets.

The incident dataset is classified into multiple buckets based on severity. The historical records from the past two years contain unplanned incidents related to the SLA violations of production systems. These incidents show variations across seasons, and monthly forecasting helps track/forewarn operations and business teams for proper support and planning. Though most predictive models benefit from long-range historical data, long-term predictions become challenging due to an increase in possible predictors over time. Moreover, a majority of ITOM issues are temporary in nature. Hence, the recently tuned models are employed to predict the upcoming four quarters in a timely manner using the past six months' data.

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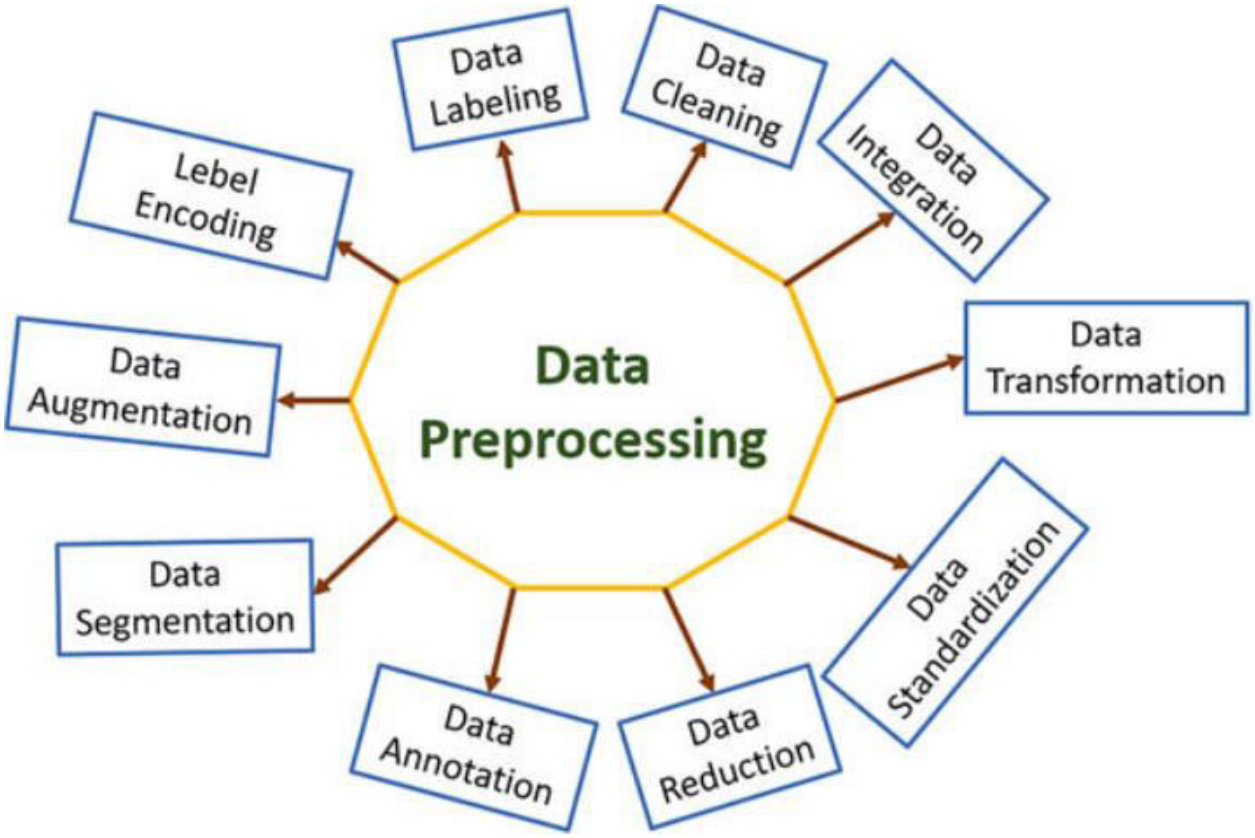

Fig 4: Conventional data preprocessing techniques in AI

4.2. Feature Engineering for Incident Prediction

Feature engineering is the process of generating predictive features from raw data in order to improve model performance. The major challenge is defining features that are strongly correlated with the target, but not too closely: an attempt to predict an exact value and thresholding at this point is very risky, whereas alerting when the value is close is prone to excessive false alarms. Each prediction target corresponds to a unique set of features extracted from data for the prediction lead-time: T-1 variables help predict T, T-2 variables predict T+1 and so on. Definitions of the derived features exploit correlations in the available data.

Five classes of features have been defined from the time-series data for use in building incident predictors: time-related features, temporal behaviour features, recent behaviour features, change in behaviour features, and third-party service features, with one or more classes being selected for each model. The first class provides information on whether an expected time or season has been reached. The second class is meant to indicate anomalies in behaviour during earlier timeframes: for example, unusual connection counts during business hours in the last week might predict an incident in the next week. The third class detects recent changes: for example, a sharp increase in interaction counts may indicate a service becoming unusually popular. Third-class features, which are taken from separate time series built from third-party services, are particularly valuable for applications requiring real-time response.

Equation 4: LSTM equations (the neural model the paper names for incident volumes)

1. **Forget gate**

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f)$$

2. **Input gate**

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i)$$

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3. **Candidate memory**

$$\tilde{c}_t = \tanh\left(W_c x_t + U_c h_{t-1} + b_c\right)$$

4. **Cell update**

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t$$

5. **Output gate**

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o)$$

6. **Hidden state**

$$h_t = o_t \odot \tanh\left(c_t\right)$$

For regression on counts:

$$\hat{y}_{t+1} = g(h_t) = W_y h_t + b_y$$

V. TIME SERIES FORECASTING MODELS

Various time series forecasting techniques have been applied in the IT domain. Auto-Regressive Integrated Moving Average models express future values as a linear function of past values, prior prediction errors, and stochastic terms. Forecasting server load up to seven days ahead leads to fewer service level agreement breaches but requires numerous past observations. Smoothing models, which combine exponential smoothing techniques and a model-based regression approach, can be effective for low-resolution weekly data for memory, CPU, and other loads. Neural network-based models can also predict system load with good accuracy when networks and system utilization are in the same range. Fourier series-based models, which predict future values of quantized resource usage of an SMP kernel based on previous usage, have been proposed for Linux systems and can optimize resource allocation.

Most time series forecasting attempts in IT have focused on a single time series. A hybrid method integrating a vector auto-regressive model for symmetric time series, with an estimation model for asymmetric load and support vector regression for error adjustment, has been applied. A multi-space multi-time forecast model addresses scaling issues of the original model by decomposing a long-term forecast into a few relatively small models, each covering a short period and a small region. A multi-level hybrid model combines an improved seasonal ARIMA model and support vector regression at the second layer to predict server workload several hours ahead, providing better results than a single model. The multi-channel feature fusion idea in computer vision aims to extract features from multiple standard image color channels but has also been extended for multivariate time series learning in other domains, notably industrial Internet.

The landscape of modern time series forecasting in IT has shifted from isolating single variables to employing sophisticated, multi-layered architectures that handle complexity with greater precision. While early efforts were limited by their narrow focus, current methodologies favor **hybridization**—such as integrating Vector Auto-Regressive (VAR) models for symmetric data with Support Vector Regression (SVR) to refine error margins. To combat the inherent scaling difficulties of long-term predictions, practitioners are increasingly adopting **multi-space, multi-time models** that decompose broad forecasts into manageable, localized segments.

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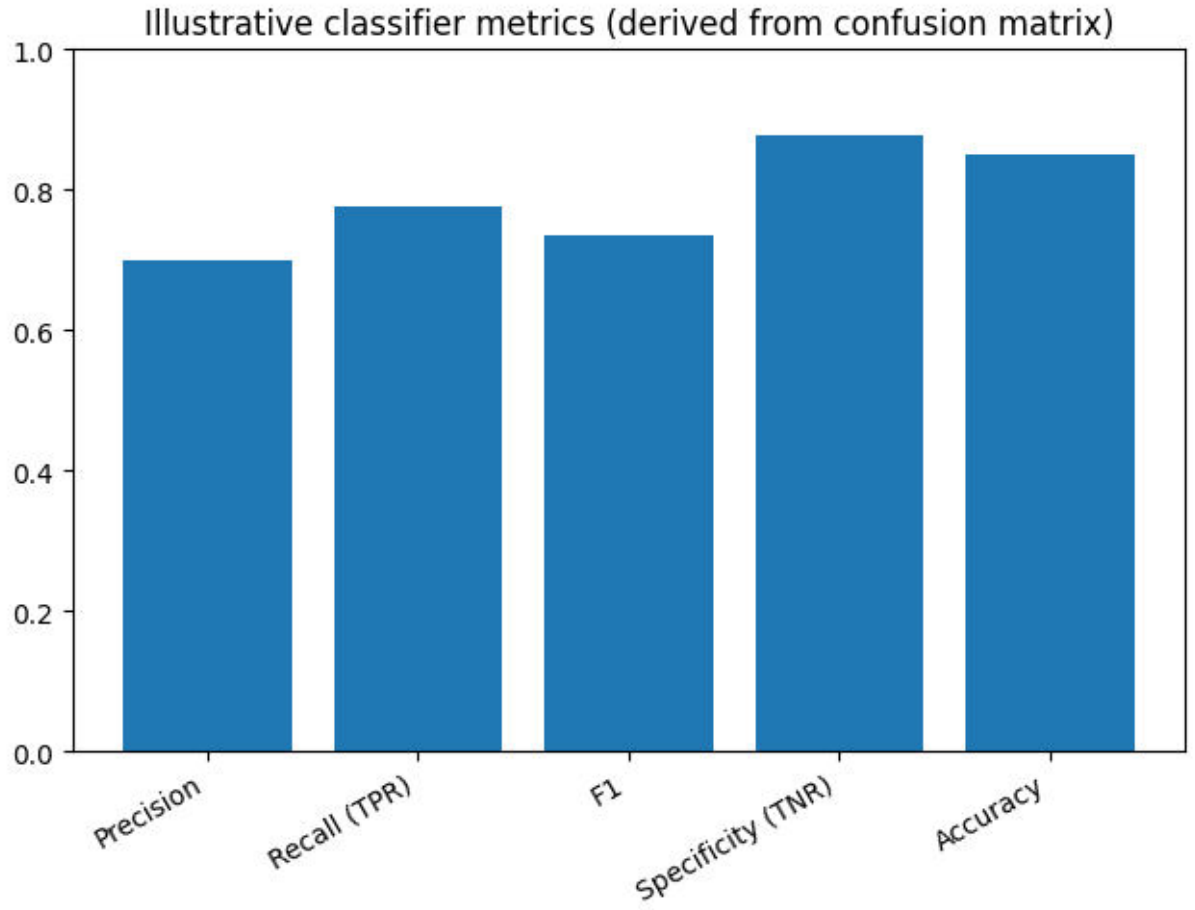

5.1. Anomaly Detection and Unsupervised Methods

Anomaly detection algorithms are used to forecast faults in a supervised manner and often excel in scenarios where failures are sporadic in nature or when known faults exist. Therefore, extensive preliminary investigation is often recommended. Furthermore, different models can be evaluated for surveillance purposes such as service tracking, anomaly detection, and forecasting, relying on the fact that models appropriate for one usage often generalize to others. Unsupervised methods used to build either thresholds or predictive capacity planning have gained popularity among businesses because they, unlike supervised models, do not depend on the availability of labelled training datasets. These methods can create alerts and thresholds on a non-7/24 basis to catch anomalies in real-time.

Data can also be leveraged to proactively address the reliability of systems rather than just their performance. Monitoring systems often ingest dozens to hundreds of metrics. Response time, throughput, error rates, and other application characteristics are usually scrutinized to ensure the systems are not degrading or misbehaving. Any drop in quality of one of the monitored metrics could jeopardize the all-important user experience. IT Operations teams monitor key indicators, defining thresholds that, when crossed, generate an alert in the company's event management solution for observation and corrective action. Therefore, when the threshold of any metric is crossed, it generates a major incident alert for the trigger.

Equation 5: Anomaly detection via rolling z-score (thresholding approach)

For a window w:

$$\mu_t = \frac{1}{w}\sum_{k=0}^{w-1} x_{t-k}$$

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$$\sigma_t = \sqrt{\frac{1}{w-1}\sum_{k=0}^{w-1}(x_{t-k} - \mu_t)^2}$$

5.2 z-score

$$z_t = \frac{x_t - \mu_t}{\sigma_t}$$

5.3 Alert rule

$$| z_t | \geq z_{\text{thr}} \Rightarrow \text{anomaly alert}$$

VI. PROACTIVE IT OPERATIONS APPLICATIONS

Proactive IT Operations Applications
The incident prediction models serve as a tool for proactive IT Operations Management. Their goal is to warn operations teams about potential incidents before they occur, reducing incident volumes and their associated negative costs—downtime costs for the business, repair costs, and user dissatisfaction. Prediction is challenging: even the "easy" task of predicting the next incident in the forecast becomes simply a classification of time—early warning systems often fail due to timing issues, leading to both false alarms and major incidents that occur without any advanced warning.

The simplest approach is to build a real-time monitoring system based on existing thresholds for anomaly detection. However, preexisting thresholds tend to be either ineffective (resulting in many undetected incidents) or useless (resulting in too many false alarms)—properly setting thresholds for comprehensive coverage is a daunting task. More fittingly, the prediction models can be used for near-term capacity planning. Algorithms exist that forecast the expected volume of incidents for any time in the future, based on historical time series data. Such anomaly detection and forecasting mechanisms can thus support capacity planning by anticipating future demand, whether for server hardware, software licenses, or other resources.

6.1. Real-Time Alerting and Thresholding

Predicting the probability of an incident on a service within a specified time window can enable proactive action before the incident occurs. Predictive alerts usually require a single model per service combination and alert for short-term predictions. Combined with a thresholding mechanism, such predictions would learn the normal behavior of a service pair and an associated labeling model could capture its abnormal behavior. More rigorously, the prediction P(Incident | S-service, S-application, current time) would only consult S-service and S-application. Depending on the adjacency of services, the solution would require more (closer services) or less (isolated from each other) thresholding models.
Threshold-triggered alerts, however, ignore the potential of correctly predicting the incident probability at time t within a longer time window. Aiming for a time-dependent function P(Incident | S-service, S-application, t), a single prediction model P(Incident | S-service, S-application, T), T being the considered time window and t ∈ T, could trigger alerts. Detecting temporal variations in the prediction beyond a certain level would be vital for alerting.

6.2. Predictive Capacity Planning

Without proactive management of physical resource capacity, increasing usage can lead to problems that may adversely affect service reliability, such as abnormal application response times, degraded performance, temporary suspension of service processing, and even complete service interruptions. Capacity management requires resources to be proactively adjusted to ensure that the service continues to operate at the required performance level. The use of time series forecasting models allows for estimation of the near-future behavior of the application or infrastructure metrics and for warning about resource saturation in advance. For example, if the memory utilization of the application server is forecasted to exceed a threshold in the next hour, the resource can be added before it is used for normal service.

A proactive feature of service capacity planning through predictive analytics is the ability to determine the resource provisioning level that minimises cost while ensuring that metrics remain within service level agreement (SLA) thresholds. Thus, a cost model that reflects the cost variation of a metric can be defined and combined with a forecast for a fixed time horizon. Cost information associated with metric forecasting deviations can then be modelled over time

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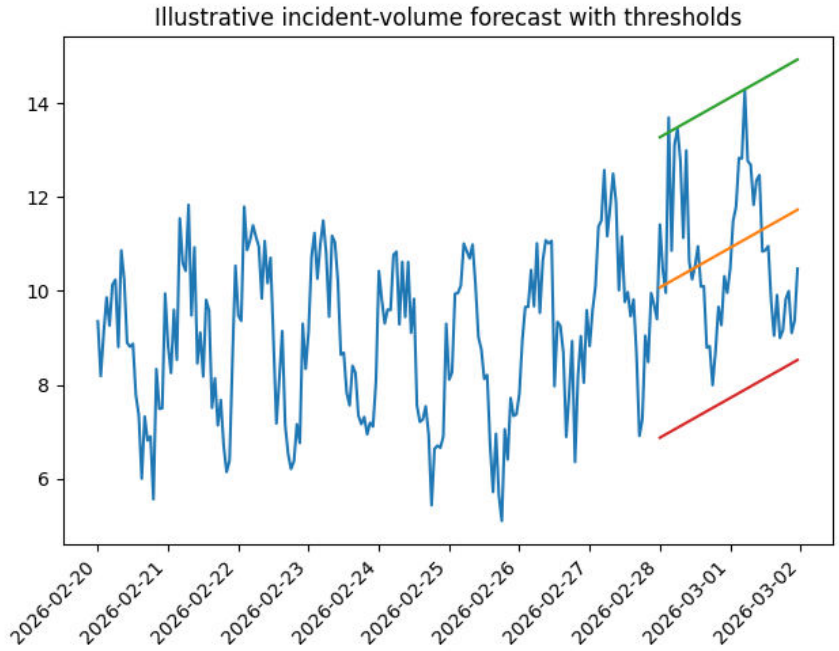
and an optimal resource level computed. Such predictive capacity planning is particularly relevant for services that are cost-sensitive and do not wish to over-provision while still respecting the defined SLA.



VII. CONCLUSION

AI-driven methods have found their way into many domains, including natural language processing, visual recognition, game playing and several others. These approaches can provide new opportunities for data-driven decision making. In IT operations management there also lies a huge potential to use AI-based prediction models to predict incidents and faults from IT systems, and thus enable proactive management of IT services. These efforts allow known service incidents to be predicted, time series anomalies to be detected in real time and the capacity scaling of IT services not only to match present demand but also future demand.

Efforts in using AI models for predictive IT operations management are still in its infancy stage. External hyperscalers and a few commercial vendors are leading the way. Research in these AI-driven predictive operations has been presented. Literature studies were made covering the area of AI methods preventing faults, and AI-based real-time alerts and anomalies preventing service incidents. Data-driven methodologies with a base in Time Series Forecasting Models, Anomaly Detection and Unsupervised methods have been examined together with their application for Proactive IT Operations management.

Item	Canonical equation	Why it appears in the paper
NDVI	NDVI = (NIR - RED)/(NIR + RED)	Normalized Difference Vegetation Index (crop greenness)
EVI	EVI = G*(NIR-RED)/(NIR + C1*RED - C2*BLUE + L)	Enhanced Vegetation Index (reduced saturation/atmos effects)
GDD	GDD = Σ max(0, (Tmax+Tmin)/2 - Tbase)	Cumulative Growing Degree Days (phenology proxy)

Table: Key equations referenced/implicit in the article (summary table)

7.1. Future Trends

Modern IT environments are growing increasingly complex due to the rise of cloud, virtualization, and automation. The number of connected devices and components continues to grow, as do the number of different vendors. Consequently, mitigating outages or service degradation has turned into a daunting task, yet ensuring IT services run without

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complications is a key condition for business continuity. IT Service Reliability Engineering (IT SRE) represents a recent move toward a proactive consideration of incidents in IT Operations Management (ITOM). When thinking about reliability, fault detection must no longer just be a reactive solution. A better approach is to predict anomalies before they develop into incidents.

In a proactive approach to incident management, predictive models could significantly improve service availability by allowing product teams to adopt a more planned approach to incident mitigation. Similar to Capacity Management, incident prediction focuses on offering alerts for service-affecting incidents, enabling teams to proactively execute preventive measures. Incident prediction uses historical IT infrastructure data to predict problems before they arise and is based on the realization that many incidents are unavoidable. Most incidents are not evident, with a large percentage being detected at the moment of customer impact or shortly after. Despite the significant investment of time and effort into incident reviews, detecting alarms from monitoring systems remains a major challenge. If a monitoring alert does not indicate an immediate impact, it is often overlooked and the associated issue is forgotten until it escalates.

REFERENCES

1. Arundel, J., Li, S. T., & Wang, J. (2020). Geographic information systems and artificial intelligence for disaster management. International Journal of Geographical Information Science, 34(10). https://doi.org/10.1080/13658816.2020.1755041
2. Garapati, R. S. (2022). Web-Centric Cloud Framework for Real-Time Monitoring and Risk Prediction in Clinical Trials Using Machine Learning. Current Research in Public Health, 2, 1346.
3. Ahmed, M., Mahmood, A. N., & Hu, J. (2016). A survey of network anomaly detection techniques. Journal of Network and Computer Applications, 60, 19–31.
4. Uday Surendra Yandamuri. (2023). An Intelligent Analytics Framework Combining Big Data and Machine Learning for Business Forecasting. International Journal Of Finance, 36(6), 682-706. https://doi.org/10.5281/zenodo.18095256
5. Aljawarneh, S., Aldwairi, M., & Yassein, M. B. (2018). Anomaly-based intrusion detection system through feature selection analysis and building hybrid efficient model. Journal of Computational Science, 25, 152–160.
6. Kummari, D. N. (2023). Energy Consumption Optimization in Smart Factories Using AI-Based Analytics: Evidence from Automotive Plants. Journal for Reattach Therapy and Development Diversities. https://doi. org/10.53555/jrtdd. v6i10s (2), 3572.
7. Bates, D. W., Saria, S., Ohno-Machado, L., et al. (2014). Big data in health care. Health Affairs, 33(7), 1123–1131.
8. Keerthi Amistapuram. (2023). Privacy-Preserving Machine Learning Models for Sensitive Customer Data in Insurance Systems. Educational Administration: Theory and Practice, 29(4), 5950–5958. https://doi.org/10.53555/kuey.v29i4.10965
9. Belle, A., Thiagarajan, R., Soroushmehr, S. M. R., et al. (2015). Big data analytics in healthcare. BioMed Research International, 2015, 370194.
10. Guntupalli, R. (2023). AI-Driven Threat Detection and Mitigation in Cloud Infrastructure: Enhancing Security through Machine Learning and Anomaly Detection. Available at SSRN 5329158.
11. Breunig, M. M., Kriegel, H. P., Ng, R. T., & Sander, J. (2000). LOF: Identifying density-based local outliers. ACM SIGMOD Record, 29(2), 93–104.
12. Unifying Data Engineering and Machine Learning Pipelines: An Enterprise Roadmap to Automated Model Deployment. (2023). American Online Journal of Science and Engineering (AOJSE) (ISSN: 3067-1140) , 1(1). https://aojse.com/index.php/aojse/article/view/19
13. Chen, M., Mao, S., & Liu, Y. (2014). Big data: A survey. Mobile Networks and Applications, 19(2), 171–209.
14. Siva Hemanth Kolla. (2023). Deep Learning–Driven Retrieval-Augmented Generation for Enterprise ITSM Automation: A Governance-Aligned Large Language Model Architecture. Journal of Computational Analysis and Applications (JoCAAA), 31(4), 2489–2502. Retrieved from https://www.eudoxuspress.com/index.php/pub/article/view/4774
15. Cios, K. J., & Moore, G. W. (2002). Uniqueness of medical data mining. Artificial Intelligence in Medicine, 26(1–2), 1–24.
16. Kummari, D. N., & Burugulla, J. K. R. (2023). Decision Support Systems for Government Auditing: The Role of AI in Ensuring Transparency and Compliance. International Journal of Finance (IJFIN)-ABDC Journal Quality List, 36(6), 493-532.

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|| Volume 6, Issue 6, November–December 2023||

DOI:10.15662/IJRAI.2023.0606028

17. Braik, A., & Koliou, M. Artificial intelligence and machine learning-powered GIS for proactive disaster resilience in a changing climate. Journal of Spatial Science, 69(1).
18. Varri, D. B. S. (2023). Advanced Threat Intelligence Modeling for Proactive Cyber Defense Systems. Available at SSRN 5774926.
19. Dwork, C. (2008). Differential privacy. ICALP Proceedings, 1–12.
20. Bandi, V. D. V. K. (2023). Production-Grade Machine Learning Pipelines For Healthcare Predictive Analytics. South Eastern European Journal of Public Health, 189–205. Retrieved from https://www.seejph.com/index.php/seejph/article/view/7057
21. Kolla, S. K. (2021). Architectural Frameworks for Large-Scale Electronic Health Record Data Platforms. Current Research in Public Health, 1(1), 1–19. Retrieved from https://www.scipublications.com/journal/index.php/crph/article/view/1372
22. Fawcett, T. (2006). An introduction to ROC analysis. Pattern Recognition Letters, 27(8), 861–874.
23. Maguluri, K. K., Pandugula, C., Kalisetty, S., & Mallesham, G. (2022). Advancing Pain Medicine with AI and Neural Networks: Predictive Analytics and Personalized Treatment Plans for Chronic and Acute Pain Managements. Journal of Artificial Intelligence and Big Data, 2(1), 112-126.
24. Garapati, R. S. (2022). AI-Augmented Virtual Health Assistant: A Web-Based Solution for Personalized Medication Management and Patient Engagement. Available at SSRN 5639650.
25. Goldstein, M., & Uchida, S. (2016). A comparative evaluation of unsupervised anomaly detection algorithms. Pattern Recognition, 64, 206–223.
26. Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep learning. MIT Press.
27. Segireddy, A. R. (2021). Containerization and Microservices in Payment Systems: A Study of Kubernetes and Docker in Financial Applications. Universal Journal of Business and Management, 1(1), 1–17. Retrieved from https://www.scipublications.com/journal/index.php/ujbm/article/view/1352
28. He, J., Baxter, S. L., Xu, J., et al. (2019). The practical implementation of AI in healthcare. Nature Medicine, 25(1), 30–36.
29. Inala, R. AI-Powered Investment Decision Support Systems: Building Smart Data Products with Embedded Governance Controls.
30. Hripcsak, G., & Albers, D. J. (2013). Next-generation phenotyping. JAMIA, 20(1), 117–121.
31. Gottimukkala, V. R. R. (2021). Digital Signal Processing Challenges in Financial Messaging Systems: Case Studies in High-Volume SWIFT Flows.
32. Iglewicz, B., & Hoaglin, D. C. (1993). How to detect and handle outliers. ASQC.
33. Johnson, A. E. W., Pollard, T. J., Shen, L., et al. (2016). MIMIC-III database. Scientific Data, 3, 160035.
34. Yandamuri, U. S. (2022). Big Data Pipelines for Cross-Domain Decision Support: A Cloud-Centric Approach. International Journal of Scientific Research and Modern Technology, 1(12), 227–237. https://doi.org/10.38124/ijsrmt.v1i12.1111
35. Kimball, R., & Caserta, J. (2004). The data warehouse ETL toolkit. Wiley.
36. Davuluri, P. N. Integrating Artificial Intelligence into Event-Driven Financial Crime Compliance Platforms.
37. Kriegel, H. P., Kröger, P., Schubert, E., & Zimek, A. (2009). Outlier detection in axis-parallel subspaces. PKDD Proceedings, 831–838.
38. Kummari, D. N. (2023). AI-Powered Demand Forecasting for Automotive Components: A Multi-Supplier Data Fusion Approach. European Advanced Journal for Emerging Technologies (EAJET)-p-ISSN 3050-9734 en e-ISSN 3050-9742, 1(1).
39. LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521(7553), 436–444.
40. Li, Y., Chen, C. Y., Wasserman, W. W., & Ramani, A. K. (2016). Deep feature selection. Bioinformatics, 32(5), 743–750.
41. Varri, D. B. S. (2022). A Framework for Cloud-Integrated Database Hardening in Hybrid AWS-Azure Environments: Security Posture Automation Through Wiz-Driven Insights. International Journal of Scientific Research and Modern Technology, 1(12), 216-226.
42. Malhotra, P., Vig, L., Shroff, G., & Agarwal, P. (2015). Long short-term memory networks for anomaly detection. ESANN Proceedings.
43. Kalisetty, S., Vankayalapati, R. K., Reddy, L., Sondinti, K., & Valiki, S. (2022). AI-Native Cloud Platforms: Redefining Scalability and Flexibility in Artificial Intelligence Workflows. Linguistic and Philosophical Investigations, 21(1), 1-15.
44. Garapati, R. S. (2023). Optimizing Energy Consumption in Smart Build-ings Through Web-Integrated AI and Cloud-Driven Control Systems.

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|| Volume 6, Issue 6, November–December 2023||

DOI:10.15662/IJRAI.2023.0606028

45. Miotto, R., Wang, F., Wang, S., Jiang, X., & Dudley, J. T. (2018). Deep learning for healthcare. Briefings in Bioinformatics, 19(6), 1236–1246.
46. Kushvanth Chowdary Nagabhyru. (2023). Accelerating Digital Transformation with AI Driven Data Engineering: Industry Case Studies from Cloud and IoT Domains. Educational Administration: Theory and Practice, 29(4), 5898–5910. https://doi.org/10.53555/kuey.v29i4.10932
47. Murphy, S. N., Weber, G., Mendis, M., et al. (2010). i2b2 platform. JAMIA, 17(2), 124–130.
48. Guntupalli, R. (2023). Optimizing Cloud Infrastructure Performance Using AI: Intelligent Resource Allocation and Predictive Maintenance. Available at SSRN 5329154.
49. Patcha, A., & Park, J. M. (2007). An overview of anomaly detection techniques. Computer Networks, 51(12), 3448–3470.
50. Pedregosa, F., Varoquaux, G., Gramfort, A., et al. (2011). Scikit-learn. Journal of Machine Learning Research, 12, 2825–2830.
51. Aitha, A. R. (2023). CloudBased Microservices Architecture for Seamless Insurance Policy Administration. International Journal of Finance (IJFIN)-ABDC Journal Quality List, 36(6), 607-632.
52. Rajkomar, A., Oren, E., Chen, K., et al. (2018). Scalable deep learning with EHRs. NPJ Digital Medicine, 1, 18.
53. Avinash Reddy Segireddy. (2022). Terraform and Ansible in Building Resilient Cloud-Native Payment Architectures. International Journal of Intelligent Systems and Applications in Engineering, 10(3s), 444–455. Retrieved from https://www.ijisae.org/index.php/IJISAE/article/view/7905.
54. Ringberg, H., Soule, A., Rexford, J., & Diot, C. (2007). Sensitivity of PCA for anomaly detection. SIGMETRICS Proceedings.
55. Koppolu, H. K. R., Sheelam, G. K., & Komaragiri, V. B. (2023). Autonomous Telecommunication Networks: The Convergence of Agentic AI and AI-Optimized Hardware. International Journal of Science and Research (IJSR), 12(12), 2253-2270.
56. Ruff, L., Vandermeulen, R. A., Görnitz, N., et al. (2018). Deep one-class classification. ICML Proceedings.
57. Rongali, S. K. (2023). Explainable Artificial Intelligence (XAI) Framework for Transparent Clinical Decision Support Systems. International Journal of Medical Toxicology and Legal Medicine, 26(3), 22-31.
58. Salfner, F., Lenk, M., & Malek, M. (2010). Survey of failure prediction methods. ACM Computing Surveys, 42(3), 1–42.
59. Nagubandi, A. R. (2023). Advanced Multi-Agent AI Systems for Autonomous Reconciliation Across Enterprise Multi-Counterparty Derivatives, Collateral, and Accounting Platforms. International Journal of Finance (IJFIN)-ABDC Journal Quality List, 36(6), 653-674.
60. Schölkopf, B., Platt, J. C., Shawe-Taylor, J., et al. (2001). Estimating the support of a high-dimensional distribution. Neural Computation, 13(7), 1443–1471.
61. Kalisetty, S., & Ganti, V. K. A. T. (2019). Transforming the Retail Landscape: Srinivas's Vision for Integrating Advanced Technologies in Supply Chain Efficiency and Customer Experience. Online Journal of Materials Science, 1, 1254.
62. Sipos, R., Fradkin, D., Moerchen, F., & Wang, Z. (2014). Log-based predictive maintenance. KDD Proceedings.
63. Meda, R. (2023). Intelligent Infrastructure for Real-Time Inventory and Logistics in Retail Supply Chains. Educational Administration: Theory and Practice.
64. Kolla, S. K. (2021). Designing Scalable Healthcare Data Pipelines for Multi-Hospital Networks. World Journal of Clinical Medicine Research, 1(1), 1–14. Retrieved from https://www.scipublications.com/journal/index.php/wjcmr/article/view/1376
65. Bandi, V. D. V. K. (2023). Cloud-Native Model Lifecycle Management for Enterprise AI Systems. International Journal of Scientific Research and Modern Technology, 2(12), 78–90. https://doi.org/10.38124/ijsrmt.v2i12.1236
66. Inala, R. Revolutionizing Customer Master Data in Insurance Technology Platforms: An AI and MDM Architecture Perspective.
67. Tibshirani, R. (1996). Regression shrinkage and selection via the Lasso. Journal of the Royal Statistical Society B, 58(1), 267–288.
68. Gottimukkala, V. R. R. (2023). Privacy-Preserving Machine Learning Models for Transaction Monitoring in Global Banking Networks. International Journal of Finance (IJFIN)-ABDC Journal Quality List, 36(6), 633-652.
69. Tukey, J. W. (1977). Exploratory data analysis. Addison-Wesley.
70. AI Powered Fraud Detection Systems: Enhancing Risk Assessment in the Insurance Sector. (2023). American Journal of Analytics and Artificial Intelligence (ajaai) With ISSN 3067-283X, 1(1). https://ajaai.com/index.php/ajaai/article/view/14

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|| Volume 6, Issue 6, November–December 2023||

DOI:10.15662/IJRAI.2023.0606028

71. Weber, G. M., Mandl, K. D., & Kohane, I. S. (2014). Finding the missing link for big biomedical data. JAMIA, 21(1), 1–3.
72. Kolla, S. H. (2021). Rule-Based Automation for IT Service Management Workflows. Online Journal of Engineering Sciences, 1(1), 1–14. Retrieved from https://www.scipublications.com/journal/index.php/ojes/article/view/1360
73. Wilkinson, M. D., Dumontier, M., Aalbersberg, I. J., et al. (2016). FAIR Guiding Principles. Scientific Data, 3, 160018.
74. Zhang, Y., & Yang, Q. (2021). A survey on multi-task learning. IEEE Transactions on Knowledge and Data Engineering, 34(12), 5586–5609.
75. Meda, R. (2023). Developing AI-Powered Virtual Color Consultation Tools for Retail and Professional Customers. Journal for ReAttach Therapy and Developmental Diversities. https://doi. org/10.53555/jrtdd. v6i10s (2), 3577.
76. Almadhoun, R., Kadadha, M., Al-Fuqaha, A., & Guizani, M. (2021). A user-centric blockchain-based system for incident response in the era of IoT. Internet of Things, 14, 100371. https://doi.org/10.1016/j.iot.2021.100371
77. Kalisetty, S. (2023). The Role of Circular Supply Chains in Achieving Sustainability Goals: A 2023 Perspective on Recycling, Reuse, and Resource Optimization. Reuse, and Resource Optimization (June 15, 2023).
78. Little, R. J. A., & Rubin, D. B. (2002). Statistical analysis with missing data. Wiley.
79. Siva Hemanth Kolla. (2022). Knowledge Retrieval Systems for Enterprise Service Environments. International Journal of Intelligent Systems and Applications in Engineering, 10(3s), 495–506. Retrieved from https://ijisae.org/index.php/IJISAE/article/view/8037
80. Bishop, C. M. (1994). Novelty detection and neural network validation. IEE Proceedings, 141(4), 217–222.
81. Rongali, S. K. (2022). AI-Driven Automation in Healthcare Claims and EHR Processing Using MuleSoft and Machine Learning Pipelines. Available at SSRN 5763022.
82. Cook, D. J., & Holder, L. B. (2006). Mining graph data. Wiley.
83. Box, G. E. P., Jenkins, G. M., & Reinsel, G. C. (2015). Time series analysis: Forecasting and control. Wiley.
84. Amistapuram, K. (2022). Fraud Detection and Risk Modeling in Insurance: Early Adoption of Machine Learning in Claims Processing. Available at SSRN 5741982.
85. Kumar, A., Gupta, P., & Singh, R. (2023). Sentiment analysis methods for proactive brand reputation risk management. International Journal of Information Management Data Insights, 3(1).
86. Ramesh Inala. (2023). Big Data Architectures for Modernizing Customer Master Systems in Group Insurance and Retirement Planning. Educational Administration: Theory and Practice, 29(4), 5493–5505. https://doi.org/10.53555/kuey.v29i4.10424
87. Aggarwal, C. C. (2017). Outlier analysis (2nd ed.). Springer.
88. Davuluri, P. N. AI-Augmented Sanctions Screening: Enhancing Accuracy and Latency in Real Time Compliance Systems.
89. Bifet, A., & Gavalda, R. (2007). Learning from time-changing data with adaptive windowing. SDM Proceedings.
90. Nagabhyru, K. C. (2023). From Data Silos to Knowledge Graphs: Architecting CrossEnterprise AI Solutions for Scalability and Trust. Available at SSRN 5697663.
91. Zaharia, M., Chowdhury, M., Franklin, M. J., et al. (2010). Spark: Cluster computing. HotCloud Proceedings.
92. Avinash Reddy Aitha. (2022). Deep Neural Networks for Property Risk Prediction Leveraging Aerial and Satellite Imaging. International Journal of Communication Networks and Information Security (IJCNIS), 14(3), 1308–1318. Retrieved from https://www.ijcnis.org/index.php/ijcnis/article/view/8609
93. Goutham Kumar Sheelam, Hara Krishna Reddy Koppolu. (2022). Data Engineering And Analytics For 5G-Driven Customer Experience In Telecom, Media, And Healthcare. Migration Letters, 19(S2), 1920–1944. Retrieved from https://migrationletters.com/index.php/ml/article/view/11938
94. Alenezi, M., & Akour, M. AI-driven innovations in software engineering: A review of current practices and future directions. Applied Sciences, 15(3), 1344. https://doi.org/10.3390/app15031344 Cited by: 149
95. Meda, R. (2023). Data Engineering Architectures for Scalable AI in Paint Manufacturing Operations. European Data Science Journal (EDSJ) p-ISSN 3050-9572 en e-ISSN 3050-9580, 1(1).
96. Kalisetty, S., & Singireddy, J. (2023). Optimizing Tax Preparation and Filing Services: A Comparative Study of Traditional Methods and AI Augmented Tax Compliance Frameworks. Available at SSRN 5206185.
97. Albert, B. Proactive cloud operations: Leveraging predictive orchestration and generative AI for observability and incident mitigation. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.6069389
98. Gottimukkala, V. R. R. (2022). Licensing Innovation in the Financial Messaging Ecosystem: Business Models and Global Compliance Impact. International Journal of Scientific Research and Modern Technology, 1(12), 177-186.