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An Overview on KSK Approach: AI-Driven IoT Based Decision Making System

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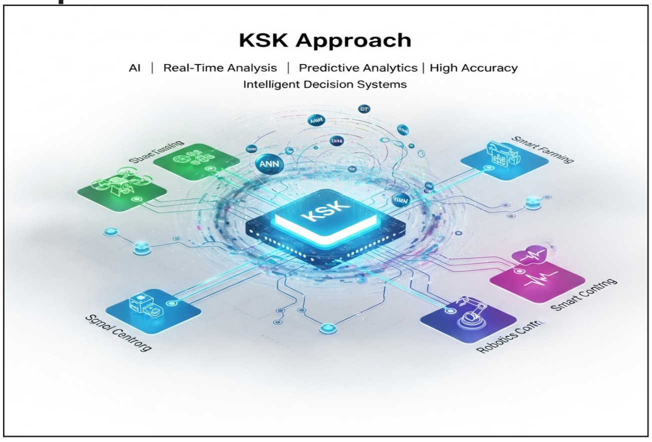
ABSTRACT

The heart of the system is the KSK approach in decision-making. The proliferation of data from interconnected devices necessitates intelligent decision-making, moving beyond traditional, human-dependent IoT systems. The KSK approach utilizes AI-driven algorithms (like ANN, DT and KNN) to analyze data collected by IoT sensors, providing instantaneous knowledge and decision-making capabilities. By enabling localized data processing (edge intelligence), the KSK approach reduces latency and enhances operational efficiency in specialized applications like smart farming, patient monitoring, and robotic control. It offers a robust framework for improving accuracy (ranging from 87% to over 99% in various applications) by providing a synergistic mix of AI and IoT technologies. The Key Focus Areas: Real-time analysis, predictive analytics, intelligent decision systems, and high accuracy. The KSK approach integrates Artificial Intelligence (AI) with the Internet of Things (IoT) to enable autonomous, real-time, and high-accuracy decision-making, often achieving up to 99.9% accuracy. This methodology transforms raw data into actionable intelligence for diverse sectors, including healthcare, smart agriculture, and robotics, by leveraging machine learning algorithms. It enhances decision-making in healthcare, agriculture, and manufacturing by analyzing data from sensors to provide insights, reduce operational costs, and improve reliability. The framework provides real-time analytics, lower operational costs, improved safety, and personalized experiences. Initiated by Dr. Kutubuddin S. Kazi, the approach is designed for scenarios where intelligent, automated, and swift decision-making is critical.

Keywords: KSK Approach, AI, IoT, AIIoT, ANN, DT, K-NN

Graphical Abstract



Introduction

The Internet of Things has already connected billions of devices worldwide, from household thermostats to industrial sensors, generating an unprecedented flood of data. Yet data alone is merely raw potential. What transforms this potential into actionable intelligence is the infusion of artificial intelligence—the cognitive capabilities that can interpret patterns, learn from experience, and make decisions with minimal human intervention. When these two technological revolutions meet, something transformative emerges: systems that not only collect information but also understand it, respond to it, and improve through continuous learning.[1]

At its core, an AI-driven IoT decision-making system (KSK Approach) operates through a sophisticated layering of technologies that work in concert. The foundation consists of the IoT infrastructure itself—the sensors, actuators, and connected devices that serve as the system's sensory organs. These devices collect data from their environment: temperature readings, pressure measurements, movement patterns, chemical compositions, audio signals, and countless other parameters depending on their application. A single smart factory might deploy thousands of such sensors, each feeding streams of information into the central system at velocities and volumes that would overwhelm human analysts.[2,3]

The next layer involves data processing and aggregation, where raw measurements are cleaned, normalized, and prepared for analysis. This stage often occurs at the network edge, close to where the data is generated, allowing rapid initial processing that can trigger immediate responses. A sensor detecting an abnormal vibration in a motor might instantly trigger a shut-off command, all within milliseconds—too fast for data to travel to a distant cloud server and back. Edge computing thus provides the responsiveness that many critical applications demand.[4,5]

The intelligence layer sits atop this infrastructure, housing the machine learning models and AI algorithms that transform processed data into decisions. These systems employ various approaches depending on the task at hand. Some use supervised learning, trained on historical data to recognize specific patterns or classify situations into predefined categories. Others employ reinforcement learning, acquiring decision-making capabilities through trial-and-error interactions with their environment, optimizing for long-term rewards. Deep learning architectures excel at processing unstructured data from multiple sources, complex patterns that simpler algorithms might miss. The choice of approach depends on factors including the nature of the decision being made, the amount and quality of available training data, and the real-time requirements of the application.[6]

Perhaps the most significant contribution of AI to IoT systems is the transition from reactive to predictive decision-making. Traditional automation follows rigid rules: if temperature exceeds threshold X, activate cooling; if pressure drops below Y, sound an alarm. While effective for known failure modes, this approach cannot anticipate novel problems or adapt to changing conditions. It waits for problems to manifest before responding.[7]

AI-driven systems fundamentally alter this dynamic. By learning from historical data, these systems develop models of normal operation and can identify deviations before they escalate into failures. When a machine's vibration signature begins to shift subtly—a change so gradual it would escape human notice or appear insignificant in isolation—the AI recognizes the pattern as consistent with developing bearing wear. The system can then schedule maintenance during planned downtime, order necessary parts, and allocate technician time, all without waiting for catastrophic failure.[8,9] The applications of AIIoT are shown in Figure 1.

This predictive capability extends far beyond equipment maintenance. Supply chain systems can anticipate demand fluctuations based on social media trends, weather forecasts, and economic indicators, adjusting inventory and production schedules proactively. Retail environments analyze foot traffic patterns, conversion rates, and external factors to optimize staffing and merchandising decisions in real time. Healthcare monitoring systems detect early warning signs of patient deterioration, enabling intervention hours or days before a crisis would otherwise occur.[10,11]

The economic implications are substantial. Predictive maintenance alone is projected to generate billions in savings across industries by reducing unplanned downtime, extending equipment lifespan, and optimizing maintenance resource allocation. When extended across the full spectrum of AI-driven IoT applications—from energy management to quality control to customer experience—the transformation represents one of the most significant productivity opportunities of the current technological era.[12]

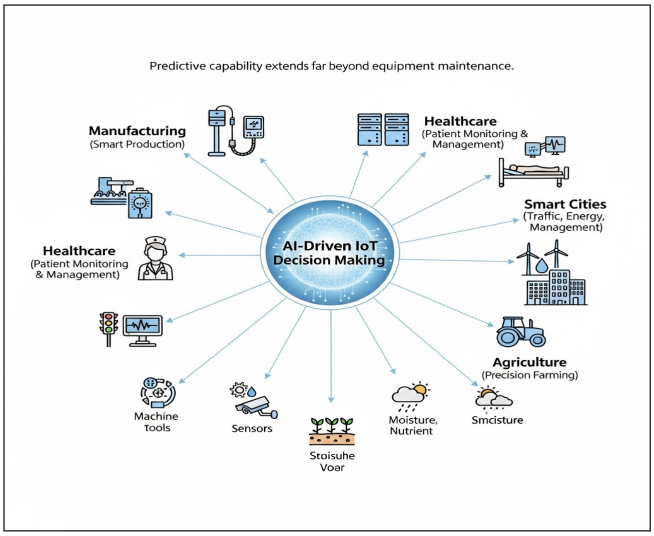


Figure 1.AIIoT Applications

The practical applications of AI-driven IoT decision-making span virtually every industry, each finding unique ways to leverage this technological convergence for competitive advantage. In manufacturing, these systems orchestrate what the industry calls "smart production". A network of sensors monitors every aspect of the production process, from machine tool wear to ambient conditions to product quality metrics. AI systems integrate this information to optimize production schedules in real time, adjusting parameters autonomously when conditions change. When a machine requires unexpected maintenance, the system automatically redistributes its workload to other equipment, resequences orders to meet deadlines, and updates delivery commitments accordingly. The result is production that adapts fluidly to disruptions while maintaining efficiency and quality standards.[13]

Healthcare offers perhaps the most consequential applications. Continuous monitoring systems equipped with AI can track patient vital signs through wearable devices, analyzing streams of data to detect patterns indicating complications. Sepsis prediction algorithms have demonstrated the ability to identify patients at risk hours before clinical criteria are met, enabling earlier treatment and significantly improving outcomes. In hospitals, AI-driven systems optimize staff scheduling, equipment allocation, and patient flow based on predicted admission rates and real-time occupancy data. For chronic disease management, connected devices monitor patient conditions between doctor visits, alerting care teams when intervention might be needed.[12]

Smart cities provide another compelling example of these systems operating at scale. Transportation networks employing AI analyze traffic data from cameras, sensors, and connected vehicles to optimize signal timing, reducing congestion and emissions. Energy grids use IoT sensors combined with AI to balance load distribution, integrate renewable sources effectively, and predict demand patterns. Water utilities employ smart sensors to detect leaks and monitor quality and pressure management, reducing waste and ensuring service reliability. These systems operate continuously, making millions of decisions daily that collectively shape urban life for millions of residents.[10]

Agricultural applications demonstrate how AI-driven IoT can address fundamental challenges in food production. Sensors measure soil moisture, nutrient levels, and environmental conditions across fields. AI systems process this information alongside weather forecasts, satellite imagery, and historical yield data to determine optimal irrigation, fertilization, and harvesting decisions. The result is increased crop yields with reduced resource inputs, contributing to agricultural sustainability while meeting the demands of a growing global population.

Understanding the nature of AI-driven decision-making requires grappling with an important distinction: these systems are designed to augment human decision-makers, not replace them entirely. The most effective implementations maintain meaningful human oversight while automating routine decisions and providing enhanced information for complex choices. In practice, this often means that AI systems handle the volume of operational decisions that would be impossible for humans to address individually—adjusting thousands of device parameters, responding to minor anomalies, optimizing countless small decisions that collectively determine system performance. Meanwhile, humans retain authority over strategic decisions, exception handling, and cases where judgement beyond the system's capabilities is required. The relationship is collaborative: AI handles what machines do best while humans focus on what people do best. This collaboration requires thoughtful interface design and organizational structure. Decision support systems must present information in ways that help humans understand system recommendations, question them when appropriate, and override them when context demands. Organizations must develop cultures and processes that leverage AI capabilities while maintaining human accountability. The technology alone is insufficient; successful implementation requires parallel investment in human capital and organizational adaptation.

Privacy and ethical considerations also demand human attention. AI-driven IoT systems inevitably collect vast amounts of data, often including personal information.

How this data is stored, who has access to it, and how it is used raise significant questions that require clear policies and robust governance frameworks. The potential for algorithmic bias—whether in credit decisions, hiring recommendations, or criminal justice applications—demands careful attention to training data, model behavior, and outcome monitoring. These systems make decisions that affect human lives, and the humans who design and deploy them bear responsibility for ensuring those decisions are fair, transparent, and accountable.

The KSK (Kutubuddin S Kazi) Approach is an advanced AI-driven Internet of Things (AIIoT) framework designed for autonomous, real-time decision-making, notably achieving high accuracy in healthcare (89–93%) and smart agriculture (up to 99.9%). Developed by Dr. Kutubuddin S. Kazi, it uses machine learning to convert raw sensor data into actionable insights.[1,2,3,4,5]

Key Aspects of the KSK Approach

- **Definition**: KSK (Kutubuddin S Kazi), or Knowledge-Sensors-Knowledge, refers to a cyclical process where knowledge is derived from sensors, processed by AI, and converted into actionable knowledge for decision-making.
- **AIIoT Integration**: It combines IoT (Internet of Things) sensors for data collection with Artificial Intelligence (AI) algorithms for data processing and analysis.

Key Applications:

- **Healthcare**: Used in BP monitoring and kidney disease management to provide real-time, accurate, and personalized healthcare management.
- **Smart Agriculture**: Enhances crop yields, reduces operational costs, and supports sustainable farming practices.
- **Autonomous Systems**: Applied in drones and other IoT ecosystems for increased efficiency, responsiveness, and reduced human intervention.
- **Key Components**: The approach utilizes classifiers and metrics like accuracy, precision, and recall to ensure the reliability of the decisions made.[1,2,3,4,5,6,7,8,9]

The methodology focuses on transforming raw data into intelligence, enabling systems to make faster, more reliable decisions in crucial sectors.

Methodology

The KSK (Kutubuddin S Kazi) approach usages ANN, DT and KNN algorithms. The ANN used is -3 layered structure, having layers as- Input layer, 2 Hidden Layers and Output layer. DT recommended is C4.5 and KNN with K-3. Figure 2 shows the KSK approach structure.

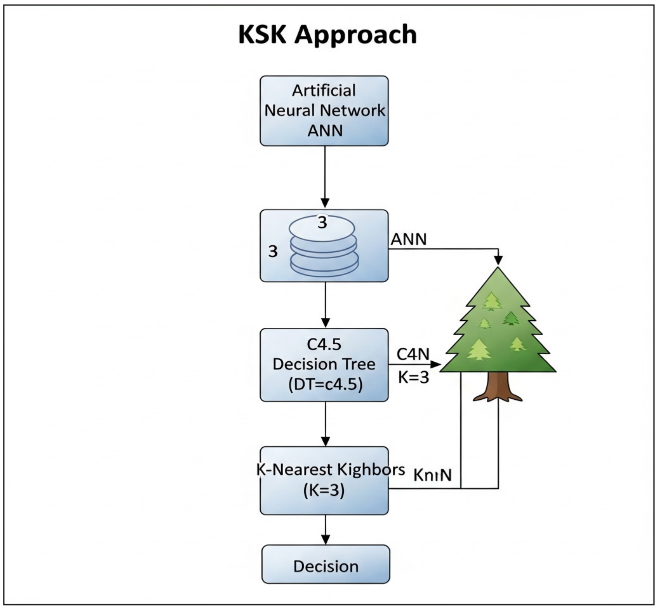


Figure 2.KSK Approach structure

ANN Structure in KSK Approach

A 3-layer ANN with two hidden layers (also considered a deep neural network) constitutes an input layer, two intermediate hidden layers (HL1, HL2), and a final output layer. Data flows forward from inputs through the hidden layers for non-linear processing—often using ReLU—to generate the prediction.[1,2,3,4,5]

Structure Details

- **Input Layer L0**: Accepts raw data; number of neurons equals the number of features.
- **Hidden Layer 1 L1**: First set of hidden nodes, often with a large number of neurons to detect initial patterns.
- **Hidden Layer 2 L2**: Second set of hidden nodes, typically extracting more abstract features from L1.
- **Output Layer L3**: Produces the prediction (e.g., probability or classification).[1,2,3,4,5]

Typical Architecture

For a classification task with input x, output-y, and neurons-n:

[Input] -> [HL1 (n1 nodes)] -> [HL2 (n2 nodes)] -> [Output]

- Each layer is fully connected to the next.
- Activation functions (like ReLU) are applied in (L1) and (L2) to enable learning complex data representations.[1,2,3]

Example: A 3-feature input, 4-node first hidden layer, 3-node second hidden layer, and 2-node output could look like (Figure 3):[1,2]

- **Input**: 3 Neurons
- **Hidden 1**: 4 Neurons
- **Hidden 2**: 3 Neurons
- **Output**: 2 Neurons

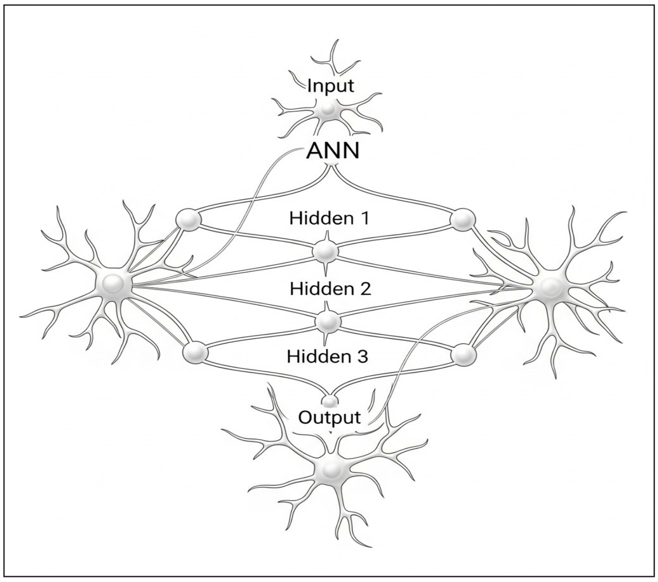


Figure 3.ANN Structure in KSK approach

For a 3-layer Artificial Neural Network (ANN) structure with two hidden layers, the standard architecture is a Feedforward Neural Network (also known as a Multilayer Perceptron).[1,2]

Training Parameters & Algorithms

- **Training Algorithm**: The most common algorithm used is Backpropagation. It works alongside an optimizer like Stochastic Gradient Descent (SGD) or Adam to minimize the network's error.
- **Learning Rate**: Typical starting values range from 0.01 to 0.1. Smaller rates (e.g., 0.001) are often used for more stable training with complex datasets to prevent overshooting the optimal weights.
- **Epochs**: Usually ranges from 10 to 500+, depending on dataset size and complexity. Practitioners often use Early Stopping to terminate training once the validation error stops improving, avoiding overfitting.
- **Batch Size**: Common values are powers of two, such as 16, 32, 64, or 128. A batch size of 32 is often the recommended starting point.[1,2,3,4,5,6,7,8,9]

Why Backpropagation is Selected

- **Foundation**: Backpropagation is based on differential calculus, specifically the Chain Rule. It calculates the gradient (direction and magnitude of change) of the loss function with respect to every weight in the network.
- **Selected Reason**: It is the standard because it efficiently allows a network to "learn" by flowing the error backward from the output layer through the hidden layers. This allows the network to adjust weights in a way that progressively reduces prediction error over time.
- **Non-Linear Mapping**: Adding two hidden layers allows the network to learn highly complex, non-linear patterns that a single layer cannot capture.

Decision Tree Structure in KSK Approach-

The DT recommended is C4.5. The C4.5 algorithm is a supervised machine learning method used to generate a decision tree for classification. Developed by Ross Quinlan as an extension of the ID3 algorithm, it is often cited as a "workhorse" in data mining due to its robustness and flexibility.[1,2,3]

Unlike its predecessor ID3, C4.5 addresses several real-world data challenges:[1,2]

- **Handles Continuous Data**: It can process numerical attributes by dynamically defining thresholds to partition values into discrete intervals (e.g., Age <= 30 vs. Age > 30).
- **Uses Gain Ratio**: Instead of simple Information Gain, C4.5 uses the Gain Ratio as its splitting criterion. This reduces the bias toward attributes with many distinct values (like unique IDs).
- **Supports Pruning**: It performs "post-pruning" to remove branches that do not contribute to predictive power, which helps prevent overfitting and simplifies the final tree.
- **Manages Missing Values**: The algorithm handles incomplete data by assigning probabilities to possible values or distributing the data across branches proportionally.[1,2,3,4,5,6,7]

How the Algorithm Works

C4.5 builds the tree top-down using a recursive "divide and conquer" approach:[1,2]

- **Select Best Attribute**: Calculate the Gain Ratio for every attribute. The one with the highest ratio is selected as the root or decision node.
- **Split Data**: Partition the dataset into subsets based on the chosen attribute's values.
- **Recursion**: Repeat the process for each subset (child node) until a stopping criterion is met—such as all samples in a branch belonging to the same class.
- **Pruning**: Once the tree is complete, the algorithm may "prune" it by replacing less useful subtrees with leaf nodes to improve accuracy on unseen data.[1,2,3,4,5]

Key Reasons to Use C4.5

- **Handles Multiple Data Types**: Unlike ID3, which only works with categorical (nominal) data, C4.5 can process both discrete and continuous attributes by creating thresholds for numerical values.

- **Reduces Bias**: It uses the Information Gain Ratio as a splitting criterion rather than simple Information Gain. This prevents the algorithm from favouring features with many unique values (like ID numbers), which often leads to overfitting.
- **Manages Missing Data**: C4.5 is capable of handling incomplete training datasets by assigning probabilities to possible values for missing attributes during the splitting process.
- **Prevents Overfitting via Pruning**: After the tree is built, C4.5 performs post-pruning. This process removes branches that add little predictive value or capture noise, resulting in a more generalized and smaller tree.
- **High Interpretability**: It can convert trained trees into sets of simple IF-THEN rules, making the model's logic transparent and easy for human users to understand.[1,2,3,4,5,6,7,8]

Table 1 represents the comparison of ID3 and C4.5 classifier in terms of Splitting criterion, Overfitting and missing values.

KNN Structure for KSK Approach:

In the K-Nearest Neighbour (KNN) algorithm, setting \(K=3\) means the algorithm classifies a new, unlabeled data point by looking at the three closest labeled data points (neighbors) in the training set.

How KNN (K=3) Works

- **Calculate Distances**: The algorithm measures the distance (commonly Euclidean or Manhattan) between the new data point and all existing points in the dataset.
- **Find Nearest Neighbours**: It identifies the 3 points with the smallest distances.
- **Majority Vote**: The algorithm checks the class labels of these 3 neighbours. The new data point is assigned to the class that appears most frequently among them.[1,2,3,4,5]

Example Scenario (K=3)

- **Data**: A new point needs to be classified as either a Square or a Triangle.
- **Neighbors**: The 3 closest points are: 2 Triangles and 1 Square.
- **Result**: The new point is classified as a Triangle because it has the majority vote (2 against 1).[1,2,3,4,5]

Key Considerations for (K=3)

- **Odd Value**: Using an odd number for K (like 3) helps avoid ties in binary classification scenarios.
- **Local Structure**: Small values of \(K\) (like 3) focus on the local structure of the data, making the model sensitive to the immediate neighborhood.
- **Performance**: (K=3) is generally more robust than (K=1), which can be noisy or overfit, but may not be as smooth as larger (K) values (e.g., (K=5) or (K=7)).[1,2,3,4,5]

In the K-Nearest Neighbors (KNN) algorithm, (K=3) means the model makes a prediction for a new data point by looking at its three closest neighbors in the training dataset.[1,2]

There isn't a single "correct" value for (K), as it is a hyperparameter that must be tuned for each specific dataset. However, (K=3) is a common choice for several reasons:[1,2]

- **Avoids Ties**: Using an odd number like 3 in binary classification (e.g., Apple vs. Banana) prevents a "tie" where both classes have an equal number of votes.
- **Reduces Noise**: Compared to (K=1), (K=3) is less sensitive to individual outliers or "noisy" data points, leading to a more stable decision.
- **Maintains Local Detail**: A small (K) like 3 keeps the decision boundary tight around local patterns, whereas a very large (K) (e.g., (K=50)) might "smooth over" important local details, leading to underfitting.[1,2,3,4,5,6]

The choice of (K) dictates the balance between sensitivity and stability in your model as shown in Table 2.

Table 1.Comparison: C4.5 vs. ID3

Feature	ID3	C4.5
Attribute Types	Categorical only	Categorical & Continuous
Splitting Criterion	Information Gain	Gain Ratio
Overfitting Control	None (grows full trees)	Post-pruning
Missing Values	Not supported	Supported via probabilities

Table 2.Impact of K Value

K Value	Effect	Performance
Small ((K=1, 3))	High sensitivity to local data and noise.	Risk of overfitting; low training error but potentially high test error.
Optimal ((K=5, 10, sqrt{n}))	Balanced; smoother decision boundaries.	Usually provides the best generalization to new data.
Large ((K > 20))	Highly generalized; leans toward the majority class of the whole dataset.	Risk of underfitting; ignores local patterns.

Discussion

The KSK (Kutubuddin S Kazi) approach combines Artificial Neural Networks (3-layered ANN), Decision Tree (C4.5), and K-Nearest Neighbors ((k=3)) to improve classification performance. It leverages C4.5 for handling numerical data and rule generation, KNN for local instance-based classification, and a 3-layered ANN for learning complex, non-linear relationships, often resulting in higher accuracy and better classification, especially with noisy datasets.

Key Components of the KSK (Kutubuddin S Kazi) Approach

- **ANN (3-Layered)**: Typically includes an input layer, one hidden layer, and an output layer. It is used for modeling non-linear, complex data patterns.
- **DT (C4.5 Algorithm)**: Builds a decision tree using entropy and information gain to split attributes, creating actionable “if-then” rules. It is effective for classification.
- **KNN ((k=3))**: A lazy learner that classifies new data points based on the majority label of the three closest neighbors, functioning well with local outliers.

Synergy in the KSK (Kutubuddin S Kazi) Approach

- **Performance**: Decision Tree (C4.5) often provides better accuracy.
- **Handling Data**: C4.5 handles numerical and categorical data well.
- **Flexibility**: The combination of these techniques (as seen in) allows for overcoming the limitations of single algorithms. For instance, highlights that a combined model (similar to KSK) can achieve higher Area Under Curve (AUC) performance compared to individual algorithms like standard KNN.
- **Rule Extraction**: The C4.5 algorithm is particularly noted for its ability to generate clear, understandable classification rules.

This combined approach is highly beneficial in scenarios requiring both high precision and interpretability. The KSK (Kutubuddin S. Kazi) approach—often referred to as the Knowledge-Sensors-Knowledge approach—is an AI-driven, Internet of Things (AIIoT) framework designed by Dr. Kutubuddin S. Kazi. It is designed to transform raw IoT data into actionable intelligence for decision-making across various sectors, including healthcare, agriculture, and infrastructure. Performance parameters within this approach are largely measured by high accuracy, precision, and recall achieved through AI algorithms (such as Decision Trees, Artificial Neural Networks, and K-Nearest Neighbours).

Core Performance Metrics of the KSK Approach

The KSK methodology, which centers on fusing data, situation assessment, and knowledge-based recommendations, is evaluated using the following performance indicators:

- **Accuracy**: The KSK approach has demonstrated high classification accuracy, with studies reporting results often ranging between 87% and 99.9% depending on the specific application.
- **Recall & Precision**: The approach consistently shows high precision and recall, often exceeding 90%, which is crucial for systems requiring high reliability.
- **Response Time**: By utilizing real-time IoT data, the approach enables quick reactions to changing conditions, minimizing delay.
- **System Security & Reliability**: The KK Approach (a security concept linked to the KSK approach) adds T-cell security concepts to increase reliability and prevent malicious node interference in IoT networks. Also Dr. Kutubuddin Kazi Suggests the KVS (Kutubuddin Vahida Sultana) Approach and DL 9dilshad-Liyakat) Security Approach along with KSK approach as a security link.
- **Energy Efficiency**: When applied to systems like electric vehicles or converters, the approach reduces voltage stress on components, thus enhancing overall system efficiency.

Application-Specific Performance

- **Smart Agriculture**: The KSK approach optimizes irrigation, fertilizer, and pest management, achieving up to 99.9% accuracy and 97.9% recall in AI-driven monitoring.
- **Healthcare Monitoring**: In kidney disease patient health monitoring, the approach provides high-accuracy diagnostic support (87%–92.5%). Similar results are reported in blood pressure monitoring (89%–93%).
- **Climate Change (Drones)**: The approach achieves 94.3% accuracy in temperature monitoring and 94.5% in (CO2}) monitoring, demonstrating its utility in situational awareness.

Advantages over Traditional Methods

- **Data Interpretation**: Unlike traditional IoT systems that struggle with data density, the KSK approach uses AI to interpret and apply data rather than just collecting it.
- **Real-time Decision Making**: It moves from static, historical analysis to dynamic, real-time insights.
- **Personalization**: The system can learn from user behavior to tailor services.
- **Resilience**: The KSK approach contributes to higher resilience and lower packet loss in network environments.

Conclusion

The KSK (Kutubuddin S Kazi) approach provides a transformative framework for implementing AI-driven IoT systems, demonstrating significant improvements in efficiency and accuracy across varied domains. It is particularly effective in enabling proactive decision-making, such as in healthcare monitoring for chronic diseases like hypertension or in optimizing agricultural yields. By marrying sensor data with intelligent algorithms, this methodology ensures reduced system downtime, improved response times, and tailored services. Future developments are poised to enhance the efficiency of these models further, securing a vital role in autonomous decision-making environments. Key Results: High-efficiency, low-latency, and actionable intelligence.

Declarations

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