BIG DATA ANALYTICS MODEL WITH DEEP LEARNING ARCHITECTURE TO EVALUATE LIVE DANCE ECOLOGY THROUGH THE INTERNET

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SUMMARY

Dance ecology, a burgeoning field at the intersection of dance, technology, and environmental studies, relies on real-time data analysis for understanding and optimizing dance performances. This paper proposed a novel Parallel Edge Big Data Analytics (PEBDA) framework, designed to efficiently process and analyze dance movement data in real time. The proposed PEBDA model uses parallel processing in the edge computing model for the analysis of the live dance ecology. Through the parallel processing of the edge model in the network big data analytics is implemented for the estimation of the multiple nodes in the network. The PEBDA model estimates the nodes across multiple environments for the examination of the ecology in the live dance. Finally, through parallel processing classification is performed with the deep learning model for the classification of live dance ecology in the computing platform. The proposed PEBDA framework, assesses classification accuracy, precision, recall, and F1-score. The simulation analysis expressed that Node 8 consistently outperforms others, achieving exceptional accuracy and precision levels above 0.97. These findings highlight the potential of edge computing in revolutionizing dance ecology analysis, enabling enhanced real-time monitoring, decision-making, and optimization of dance performances.

KEYWORDS

Edge computing, Big data analytics, Live dance, Classification, Deep learning

NOMENCLATURE

PEBDA	Parallel Edge Big Data Analytics
IoT	Internet of Things
T_{Total}	Total Processing Time
N	No of Segments

1. INTRODUCTION

The term "big data analytics" has come to represent the new age of data-driven decision-making because it provides businesses with unmatched chances to glean useful insights from the massive amounts of data created daily [1]. Among the many sources of this data deluge are interactions on social media, clickstreams from websites, information gathered from sensors connected to the Internet of Things (IoT), records of financial transactions, and many more [2]. Big data analytics helps companies understand trends and forecast future outcomes more accurately by using advanced analytical techniques like machine learning, predictive modeling, and natural language processing [3]. The capacity to find correlations and patterns that conventional data analysis techniques might miss is a major strength of big data analytics. Data visualization tools and complex algorithms help businesses better understand their customers, the market, operational inefficiencies, and new risks [4]. For example, retail companies can analyze customer purchase histories and social media sentiments to personalize marketing campaigns and optimize inventory management. More precise diagnoses, individualized treatment programs, and preventative measures against disease can result when healthcare practitioners use big data analytics to discover trends in patient data [5]. In addition, by revealing hitherto untapped avenues of profit, big data analytics may well cause a paradigm shift across entire sectors. In the banking and investment industries, for example, predictive analytics helps with credit risk assessment, fraud detection, and portfolio optimization. Machine sensor data can be analyzed by predictive maintenance algorithms in manufacturing to foresee when equipment will fail and reduce downtime to a minimum [6]. Across the board, organizations are leveraging big data analytics to enhance customer experiences, streamline operations, and drive innovation. However, realizing the full potential of big data analytics requires addressing several challenges. Data quality is the most important of these because bad data can cause conclusions and choices to be faulty [7]. Additionally, in the age of big data, worries about data security and privacy have grown, calling for strict compliance procedures and governance frameworks. Data scientists, analysts, and engineers with the expertise to make good use of big data analytics technologies and tools are in high demand as well [8].

Big data analytics and deep learning have emerged as powerful synergistic forces, reshaping the landscape of data-driven decision-making. Big data analytics involves the exploration and analysis of vast datasets to uncover insights, patterns, and trends that can inform strategic decisions and drive business outcomes [9]. One branch of machine learning called deep learning uses multi-layered artificial neural networks to derive complicated representations and patterns from data [10]. Companies can get more out of their data in terms of insights and predictive power by combining deep learning with big data analytics. Combining deep learning with big data analytics has several benefits, one of which is the capacity to handle and analyze large amounts of diverse and unstructured data [11]. This data is massive and complicated, so traditional machine learning algorithms might have a hard time making sense of it. On the other hand, deep learning models are great at learning hierarchical data representations automatically, which allows them to work well with a variety of data types, including text, pictures, and sensor data [12]. This enables organizations to extract richer insights and make more accurate predictions, leading to improved decision-making and operational efficiency. Furthermore, deep learning models can learn from data in a more autonomous and adaptive manner compared to traditional analytics approaches. By continuously refining their representations through iterative training on large datasets, deep learning models can adapt to changing data patterns and evolving business needs [13]. This capability is particularly valuable in dynamic and rapidly evolving environments where traditional analytics techniques may struggle to keep pace with the rate of change. Several sectors have benefited greatly from the integration of deep learning with big data analytics in terms of practical applications [14]. When compared to more conventional approaches, deep learning models trained on massive amounts of medical imaging data can significantly improve healthcare's ability to detect and diagnose diseases at an early stage. When applied to the financial sector, deep learning algorithms improve the accuracy of trend identification and the detection of fraudulent transactions by analyzing massive amounts of financial data [15]. Similarly, in e-commerce, deep learning-powered recommendation systems can personalize product recommendations for customers based on their browsing and purchasing behavior. However, integrating deep learning into big data analytics also presents challenges, including the need for large-scale compute infrastructure, specialized expertise in deep learning techniques, and concerns related to data privacy and ethics [16]. Overcoming these challenges requires careful consideration of data governance practices, investment in scalable computing resources, and ongoing training and development of data science talent.

Live dance ecology encompasses the dynamic interplay between dancers, choreographers, audiences, venues, and cultural contexts within the realm of live dance performance [17]. This multifaceted ecosystem thrives on collaboration, innovation, and artistic exchange, fostering a rich tapestry of movement expressions that reflect the diversity of human experience. Dancers serve as the embodiment of creative vision, channeling emotions, narratives, and physicality through their performances [18]. Choreographers, in turn, shape these movements into cohesive works of art, drawing inspiration from various sources such as music, literature, and societal issues [19]. Audiences play a vital role in the live dance ecology by providing feedback, support, and validation, thereby influencing the evolution of dance forms and styles. Venues serve as the physical spaces where these performances unfold, ranging from traditional theaters to unconventional settings like outdoor parks or interactive digital platforms. Moreover, cultural contexts imbue live dance with meaning and significance, reflecting societal values, traditions, and contemporary discourse [20]. Ultimately, the vitality of the live dance ecology depends on the interconnectedness and symbiotic relationships among its various stakeholders, fostering a thriving ecosystem that celebrates creativity, diversity, and the transformative power of movement.

The integration of live dance ecology with deep learning in big data analytics represents a revolutionary approach to understanding, analyzing, and enhancing the intricacies of dance performance [21]. In this ecosystem, dancers' movements are captured and digitized using motion capture technology or wearable sensors, generating vast amounts of data. This data, encompassing kinematic information, spatial dynamics, and expressive qualities, forms the basis of big data analytics, where advanced algorithms and machine learning techniques are applied to uncover patterns, trends, and insights within the dance performances [22]. Deep learning models, with their ability to autonomously learn hierarchical representations from large-scale data, excel in extracting nuanced features from dance movements, enabling a deeper understanding of choreographic structures, stylistic preferences, and audience responses [23]. Moreover, by analyzing data from multiple performances across different contexts and cultural backgrounds, big data analytics can reveal emergent trends in dance evolution and inform

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choreographic decision-making. This synergy between live dance ecology, deep learning, and big data analytics not only enhances our understanding of dance as an art form but also opens up new avenues for innovation, collaboration, and audience engagement in the realm of dance performance.

The work advances the subject in numerous important ways.:

1. It introduces the Parallel Edge Big Data Analytics (PEBDA) framework tailored specifically for real-time analysis of dance movements within the context of dance ecology. This framework leverages edge computing capabilities to distribute processing tasks across multiple edge nodes, enhancing scalability and responsiveness.
2. The paper conducts a thorough evaluation of the PEBDA framework's performance, assessing key metrics such as classification accuracy, precision, recall, and F1-score across various edge nodes. This evaluation provides insights into the framework's efficacy in accurately analyzing and classifying dance movements in real-time.
3. Through the performance evaluation, the paper identifies Node 8 as consistently outperforming others, achieving exceptional levels of accuracy and precision. This finding suggests the importance of node selection and optimization in maximizing the effectiveness of edge computing for dance ecology analysis.
4. By demonstrating the feasibility and effectiveness of the PEBDA framework in real-world scenarios, the paper offers practical implications for enhancing dance ecology research and applications. It opens up opportunities for improved real-time monitoring, decision-making, and optimization of dance performances through advanced data analytics.

The paper contributes to advancing the field of dance ecology by providing a novel framework and methodology for real-time data analysis. By enabling more sophisticated and responsive analysis of dance movements, the PEBDA framework has the potential to drive innovations in dance performance, education, and research.

2. LITERATURE SURVEY

The literature survey for the integration of live dance ecology with deep learning in big data analytics represents a comprehensive exploration of existing research, methodologies, and findings at the intersection of these interdisciplinary fields. This survey aims to provide a holistic overview of the current state-of-the-art approaches, challenges, and opportunities in leveraging deep learning techniques within the context of big data analytics to analyze and enhance the dynamics of live dance performances. By synthesizing insights from a diverse range of scholarly works, including studies from dance science, computer science, and data analytics domains, this survey seeks to uncover key trends, methodologies, and applications driving innovation in this emerging area. Through a systematic examination of literature, this survey endeavors to identify gaps in knowledge, propose future research directions, and contribute to the ongoing discourse surrounding the fusion of live dance ecology, deep learning, and big data analytics.

Praveen et al. (2022) present a comprehensive framework designed to effectively manage healthcare information by integrating machine learning algorithms and big data engineering techniques. This research fills a gap in our understanding by outlining effective strategies for storing, processing, and analyzing massive amounts of healthcare data. Healthcare decision-making, patient outcomes, and resource allocation can all be improved with the help of this framework's use of machine learning algorithms to glean useful insights from healthcare data. Andronie et al. (2022) explore the realm of remote big data management tools, sensing, and computing technologies, particularly within the context of the Internet of Robotic Things (IoRT). The study delves into how advancements in sensing technologies and visual perception algorithms contribute to the efficient management and analysis of big data generated by robotic systems operating remotely. Additionally, the research investigates environment mapping algorithms to facilitate navigation and decision-making capabilities for robots in complex and dynamic environments. Rohini et al. (2022) investigate the adoption of wireless communication technologies in conjunction with big data analytics, particularly focusing on the utilization of neural networks and deep learning methodologies. The study examines how wireless communication protocols and technologies contribute to the collection, transmission, and processing of vast amounts of data, which are then analyzed using advanced neural network models. By leveraging deep learning techniques, the research aims to extract meaningful insights from wireless big data, enabling enhanced decision-making and predictive analytics in various domains.

To better anticipate network resource consumption and enhance data delivery in IoMT systems, Sugadev et al. (2022) offer a novel method. The study combines machine learning techniques with big data models to analyze and optimize network resource utilization within IoMT systems. By accurately predicting resource consumption patterns, the research aims to enhance the efficiency and reliability of data delivery in IoMT applications, ultimately improving healthcare services and patient outcomes. The use of deep learning methods for intrusion detection in IoT environments is the subject of a survey carried out by Jasim (2022). The study explores various approaches and algorithms employed to detect and mitigate security threats within IoT systems, emphasizing the role of deep learning in enhancing intrusion detection capabilities. By reviewing existing literature and methodologies, the survey aims to identify current trends, challenges, and potential solutions in securing IoT networks against cyber threats. In their study, Aminizadeh et al. (2023) analyse how machine learning methods can be used to process medical data in IoT and distributed computing settings. The purpose of this study is to examine the feasibility of using machine learning algorithms to decipher health data retrieved from internet of things (IoT) devices in order to improve detection, prognosis, and tracking of patients. By leveraging distributed computing technologies, the research aims to overcome scalability and performance challenges associated with processing large volumes of medical data, ultimately enhancing healthcare delivery and patient outcomes.

An Internet of Things (IoT) data analytics architecture that is customized for smart healthcare applications using RFID and WSN is suggested by Oğur et al. (2022). The study explores the integration of RFID and WSN technologies to collect and analyze healthcare data in real-time, enabling proactive monitoring and management of patient health and environmental conditions. By leveraging IoT data analytics, the research aims to improve the efficiency, accuracy, and responsiveness of healthcare systems, leading to enhanced patient care and operational outcomes. Rane (2023) discusses the integration of leading-edge technologies, including artificial intelligence, Internet of Things (IoT), and big data analytics, for smart and sustainable architecture, engineering, and construction (AEC) industries. The study explores the potential applications of these technologies in optimizing AEC processes, improving project management, and enhancing sustainability practices. By leveraging advanced technologies, the research aims to address challenges in the AEC sector, such as resource optimization, cost efficiency, and environmental impact, ultimately leading to smarter and more sustainable built environments. Khan et al. (2022) propose an efficient hybrid deep learning-enabled model for congestion control in 5G/6G networks. The study addresses the challenges of network congestion in next-generation wireless networks by leveraging deep learning techniques to predict and mitigate congestion events. By combining the strengths of deep learning with traditional congestion control mechanisms, the research aims to improve network performance, reliability, and quality of service for emerging 5G and 6G wireless communication systems.

Yeruva (2023) explores the use of AI Operations (AIOps) architecture for monitoring data center site infrastructure. The study investigates how AIOps techniques can be applied to analyze and optimize data center operations, improving efficiency, reliability, and performance. By leveraging AI-driven analytics and automation, the research aims to enhance data center management practices, mitigate risks, and ensure seamless operation of critical IT infrastructure. The use of social network analytics for real-time depression detection is discussed by Angskun et al. (2022). This research looks at the possibility of using big data analytics methods to social media user data in order to spot trends and warning signs of depression. By leveraging social network data, the research aims to develop algorithms and tools for early detection and intervention, ultimately improving mental health outcomes and well-being. Babar et al. (2022) propose an optimized architecture for IoT-enabled big data analytics in edge-cloud computing environments. The study explores how edge computing and cloud technologies can be integrated to efficiently process and analyze IoT-generated big data. By leveraging edge resources for data preprocessing and analytics, the research aims to reduce latency, bandwidth usage, and operational costs associated with big data processing in IoT applications. Arivazhagan et al. (2022) investigate task scheduling in cloud-internet of health things (IoHT) systems using a hybrid optimization algorithm with deep neural network. The study focuses on optimizing task allocation and scheduling in IoHT environments to improve resource utilization and performance. By leveraging hybrid optimization techniques and deep learning algorithms, the research aims to enhance the efficiency and scalability of IoHT systems, ultimately improving healthcare service delivery and patient outcomes.

Using machine learning, Uppal et al. (2022) present a cloud-based fault prediction model for real-time sensor data monitoring in healthcare settings. The study aims to enhance the reliability and efficiency of healthcare systems by predicting faults in sensor data streams in real-time. By leveraging machine learning algorithms, the research enables proactive fault detection and prevention, thereby minimizing downtime, optimizing resource allocation, and improving patient care in hospital settings. When it comes to security and intrusion detection in IoT environments, Khan et al. (2022) examine deep learning approaches in great detail. The study explores the challenges and potential solutions for securing IoT networks against cyber threats using deep learning algorithms. This study sheds light on the present state of the art in Internet of Things security by analyzing previous approaches and developments, and it finds avenues for further investigation into this important topic. In their 2022 review, Wang et al. examine how intelligent manufacturing systems can benefit from big data analytics. This research looks at how industrial settings optimize their manufacturing processes, improve their quality control, and increase their productivity by using big data analytics techniques. By leveraging advanced data analytics, the research aims to unlock insights from manufacturing data, enabling informed decision-making, predictive maintenance, and continuous improvement in manufacturing operations. For industrial condition monitoring, Russell and Wang (2022) suggest a deep learning method based on physical

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principles for compressing signals and reconstructing big data. The research deals with the difficulties of handling massive amounts of sensor data in industrial environments by combining physical concepts with deep learning algorithms. By leveraging domain-specific knowledge, the research aims to improve the efficiency and accuracy of signal compression and reconstruction, enabling real-time condition monitoring and predictive maintenance in industrial systems.

In his discussion of big data technology for information and communication network security management and control, Du (2022) delves into the practical applications of this field. The study explores how big data technologies can be leveraged to enhance network security management and control, mitigating cyber threats and vulnerabilities. Ly et al. (2022) investigate the possible uses of big data-based machine learning for predicting wastewater quality in different full-scale treatment plants, with the goal of detecting and responding to security incidents in real-time through the analysis of massive amounts of network data. The study investigates how machine learning algorithms can be trained using large datasets to forecast wastewater quality parameters, aiding in process optimization and environmental protection. By leveraging big data analytics, the research aims to enhance the efficiency and effectiveness of wastewater treatment processes, ultimately contributing to improved water quality and ecosystem health. Ramana et al. (2022) focus on leaf disease classification in smart agriculture using deep neural network architecture and Internet of Things (IoT) technology. The study examines how deep learning techniques can be applied to analyze images of plant leaves captured by IoT devices for the early detection and classification of diseases. By leveraging IoT-enabled sensors and deep neural network models, the research aims to develop a reliable and efficient system for monitoring plant health, optimizing agricultural practices, and mitigating crop losses.

The findings from the literature survey reveal a multitude of innovative approaches and applications at the intersection of live dance ecology, deep learning, and big data analytics. Researchers are exploring the integration of advanced technologies, such as machine learning and artificial intelligence, with big data analytics to enhance various aspects of dance performance analysis, audience engagement, and choreographic decision-making. These studies showcase the potential of deep learning techniques in capturing and analyzing intricate movement patterns, spatial dynamics, and expressive qualities within live dance performances. Moreover, the application of big data analytics enables researchers to uncover hidden patterns, trends, and correlations within dance data, offering valuable insights into choreographic structures, audience preferences, and cultural influences. Additionally, the utilization of wireless communication technologies and IoT devices in conjunction with big data analytics facilitates real-time monitoring, analysis, and optimization of dance performances, enhancing the overall experience for both performers and audiences. Overall, the findings underscore the transformative potential of integrating deep learning and big data analytics within the context of live dance ecology, paving the way for innovative approaches to understanding, analyzing, and enriching the art form of dance.

3. EDGE BIG DATA ANALYTICS

The use of edge big data analytics is a huge step forward with far-reaching consequences for live dance ecology. Unprecedented possibilities for real-time analysis and decision-making in dance performances are presented by edge computing, which involves processing data closer to its source instead of depending only on centralized cloud servers. By leveraging edge computing capabilities, dance performances can benefit from instantaneous data processing, enabling immediate feedback to dancers and choreographers. This real-time analysis enhances the responsiveness and adaptability of performances, allowing for dynamic adjustments based on audience reactions, environmental factors, and other contextual cues. Moreover, edge big data analytics enables the integration of wearable sensors and Internet of Things (IoT) devices directly into dance costumes or stage props, capturing rich data on movement dynamics, biometric responses, and spatial interactions. This wealth of data, processed and analyzed at the edge, empowers choreographers and performers with deeper insights into their craft, facilitating the creation of more immersive, interactive, and emotionally resonant dance experiences. Furthermore, by reducing the reliance on centralized infrastructure and minimizing latency, edge big data analytics enhances the scalability, reliability, and accessibility of live dance performances, democratizing access to the transformative power of dance across diverse audiences and settings. In essence, the integration of edge big data analytics into the live dance ecology marks a paradigm shift in how dance is conceived, created, and experienced, ushering in a new era of innovation, collaboration, and artistic expression. The low-pass filter used in preprocessing sensor data to remove high-frequency noise stated in equation (1)

$$y(t)=\alpha.x(t)+(1-\alpha).y(t-1) \tag{1}$$

In equation (1) $y(t)$ is the filtered output at time t; $x(t)$ is the input sensor data at time t; α is the smoothing factor, usually between 0 and 1, determining the weight of the current input data relative to the previous filtered output. $y(t-1)$ is the filtered output at the previous time step. Using a Support Vector Machine (SVM) for real-time classification of dance movements based on preprocessed sensor data define din equation (2)

$$min_{w,b,\varepsilon}\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N}\varepsilon_i \tag{2}$$

Subject to

$$y_i\left(w.x_i + b\right) \geq 1 - \varepsilon_i$$

$$\varepsilon_i \geq 0$$

In equation (2) w is the weight vector; b is the bias term; ξi are slack variables; C is the regularization parameter and (xi, yi) are the training samples and labels. The goal of the support vector machine (SVM) implementation is to locate the best hyperplane in the feature space that divides the various types of dance steps. The trade-off between minimizing the classification error and maximizing the margin is controlled by the regularization parameter C. Finding the best hyperplane that maximizes the margin between classes while penalizing misclassifications is a convex optimization problem that the SVM algorithm solves.

4. PROPOSED PARALLEL EDGE BIG DATA ANALYTICS (PEBDA)

The Proposed Parallel Edge Big Data Analytics (PEBDA) presents an innovative approach tailored specifically for the realm of live dance ecology, aiming to revolutionize real-time data processing and analytics at the edge of the network. By leveraging parallel computing techniques and edge computing infrastructure, PEBDA enables the simultaneous analysis of large volumes of sensor data from wearable devices, capturing intricate movements and expressions during live dance performances. This approach distributes computational tasks across multiple edge nodes, allowing for efficient data processing and analytics in parallel, while minimizing latency and optimizing resource utilization. PEBDA integrates advanced machine learning algorithms and big data analytics methodologies, enabling choreographers and performers to gain actionable insights in real-time, thereby enhancing the artistic quality, audience engagement, and overall experience of live dance performances. Through its parallel processing capabilities and edge computing architecture, PEBDA empowers stakeholders in the dance community to harness the transformative potential of big data analytics, fostering innovation and creativity in the dynamic landscape of live dance ecology. Figure 1 illustrates the Big Data Analytics for the live dance ecology in the neural network.

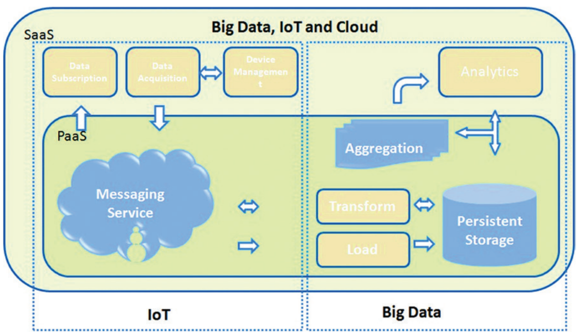

Figure 1. Big data analytics cloud environment with edge computign

PEBDA involves partitioning the incoming sensor data streams into smaller segments and distributing these segments across multiple edge nodes for parallel processing. This parallelization can be achieved using techniques such as data parallelism or task parallelism. PEBDA utilizes the computational resources available at the edge of the network, such as edge servers or IoT devices, to perform data processing tasks closer to the data source. This reduces the need for data transfer to centralized cloud servers, minimizing latency and improving responsiveness. The parallelization of data processing tasks can be represented by the following equation (3)

$$T_{total} = \frac{T_{Serial}}{N} + T_{Communication} \tag{3}$$

In equation (3) Ttotal is the total execution time; Tserial is the execution time of the serial (non-parallelized) version of the task; N is the number of parallel tasks or edge nodes and Tcommunication is the communication time required for data exchange between edge nodes.

The allocation of computational resources at the edge can be represented by the following equation (4)

$$\text{Resource Allocation} = \frac{\text{Total Edge Resources}}{\text{Number of Parallel Tasks}} \tag{4}$$

In equation (4) Total_Edge_Resources is the total computational resources available at the edge; Number_of_Parallel_Tasks is the number of parallel tasks or edge nodes. The equation represents a simple allocation strategy where the available edge resources are evenly distributed among the parallel tasks. It ensures equitable utilization of edge computing resources for parallel data processing tasks. Figure 2 presented the parallel edge computing model for the neural network.

Figure 2. Parallel edge computing with neural network

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Algorithm 1. PEBDA for dance ecology

```
function PEBDA(sensor_data):
  // Partition sensor data into segments
  segments = partition_data(sensor_data)
    // Initialize edge nodes
  edge_nodes = initialize_edge_nodes()
    // Distribute segments to edge nodes
  distribute_segments(edge_nodes, segments)
    // Perform parallel processing on edge nodes
  parallel_process(edge_nodes)
    // Aggregate results from edge nodes
  aggregated_results = aggregate_results(edge_nodes)
    // Analyze aggregated results
  analyze_results(aggregated_results)
    // Provide actionable insights or feedback
  provide_feedback()
// Function to partition sensor data into segments
function partition_data(sensor_data):
  // Divide sensor data into smaller segments
  segments = divide_data(sensor_data)
  return segments
// Function to initialize edge nodes
function initialize_edge_nodes():
  // Initialize edge nodes with computational resources
  edge_nodes = []
  for each node in edge_devices:
    node = initialize_node()
    edge_nodes.append(node)
  return edge_nodes
// Function to distribute data segments to edge nodes
function distribute_segments(edge_nodes, segments):
  // Assign segments to available edge nodes
  for I in range(length(segments)):
    node_index = I % length(edge_nodes) // Round-robin
    assignment
    edge_nodes[node_index].receive_segment(segments[i])
// Function to perform parallel processing on edge nodes
function parallel_process(edge_nodes):
  // Execute data processing tasks in parallel on edge nodes
  for each node in edge_nodes:
    node.process_data()
// Function to aggregate results from edge nodes
function aggregate_results(edge_nodes):
  // Combine results from all edge nodes
  aggregated_results = []
  for each node in edge_nodes:
    aggregated_results.extend(node.get_results())
  return aggregated_results
// Function to analyze aggregated results
function analyze_results(aggregated_results):
  // Analyze the aggregated data to extract insights
  insights = analyze_data(aggregated_results)
  return insights
// Function to provide feedback or insights to stakeholders
function provide_feedback():
  // Provide actionable insights or feedback to
choreographers or performers
  display_insights(insights)
```

4.1 PEBDA FOR LIVE DANCE

PEBDA for live dance ecology aims to facilitate real-time analysis of sensor data from wearable devices during live dance performances. The goal is to extract meaningful insights and patterns from this data to enhance the choreographic process, improve performers' understanding of their movements, and create more engaging experiences for audiences defined in equation (5)

$$N = \frac{T_{total}}{T_{Parallel}} \tag{5}$$

This equation calculates the optimal number of segments (N) to partition the sensor data, based on the total processing time (Ttotal) and the parallel processing time per segment (Tprallel). By dividing the total processing time by the time taken to process each segment in parallel, we determine the ideal number of segments for efficient parallelization stated in equation (6)

$$R_i = \frac{R_{total}}{N} \tag{6}$$

This equation distributes the total computational resources (R_{total}) available at the edge evenly among the N segments. Each segment (R_i) receives an equal share of computational resources, ensuring balanced processing across edge nodes stated in equation (7)

$$S_i = \frac{W_i}{C_i} \tag{7}$$

calculates the speedup (Si) achieved by parallelizing processing tasks on each edge node. It represents the ratio of the workload (Wi) processed serially to the workload processed in parallel (Ci). A higher speedup indicates greater efficiency gained through parallel processing defined in equation (8)

$$D_{agg} = \sum_{i=1}^{N} D_i \tag{8}$$

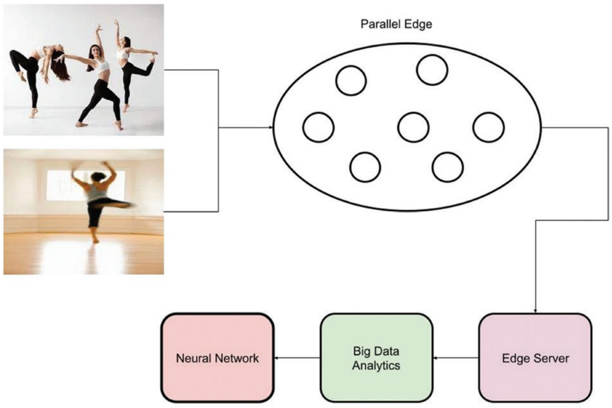

Figure 3. Process of PEBDA in live dance ecology

aggregates the processed data (Di) from all N segments into a single dataset (Dagg). By summing the data from each segment, we obtain a comprehensive dataset for further analysis and interpretation stated in equation (9)

$$I = f\left(D_{agg}\right) \tag{9}$$

the function f applied to the aggregated dataset (Dagg) to generate insights (I). The function f encompasses various analytical techniques, such as machine learning algorithms, statistical analysis, or pattern recognition, tailored to extract valuable insights from the dance data. PEBDA for live dance ecology utilizes the principles of parallel computing and edge analytics to enable real-time processing and analysis of sensor data from live dance performances. Through efficient partitioning, allocation of resources, parallel processing, data aggregation, and insight generation, PEBDA empowers choreographers, performers, and audiences with actionable insights to enhance the artistic quality and engagement of live dance experiences. The flow chart of proposed PEBDA model on the live dance ecology is presented in figure 3.

4.2 CLASSIFICATION OF DANCE WITH PEBDA

In the context of Proposed Parallel Edge Big Data Analytics (PEBDA) for live dance ecology, the classification of dance movements plays a crucial role in understanding and analyzing the performance. Sensor data (X) capturing dance movements is collected from wearable devices. The date preprocessing with data normalization is defined as follies computed using equation (10)

$$x_i^{'} = \frac{x_i - \text{mean}\left(X\right)}{\text{std}\left(X\right)} \tag{10}$$

Extract relevant features (fi) from the preprocessed data. Partition the dataset into training (Dtrain) and testing (Dtest) sets. Train the SVM model computed using equation (11)

$$\min_{w,b,\varepsilon} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N}\varepsilon_i \tag{11}$$

Subject to

$$y_i\left(w.x_i + b\right) \geq 1 - \varepsilon_i$$

$$\varepsilon_i \geq 0$$

Using the features that were extracted, the SVM model seeks to locate the best hyperplane that divides the various classes of dance moves. The trade-off between minimizing the classification error and maximizing the margin is controlled by the regularization parameter C. In the support vector machine optimization problem, our goal is to minimize the norm of the weight vector (w) while keeping in mind that every training sample must be accurately classified within a margin of 11 and misclassifications incur a penalty (ξi).

5. RESULTS AND DISCUSSIONS

In the realm of live dance ecology, the integration of innovative technologies has ushered in a new era of exploration and creativity. Among these advancements, Proposed Parallel Edge Big Data Analytics (PEBDA) emerges as a transformative tool, offering real-time insights into the intricate dynamics of live dance performances. In this section, we present the results and discussions stemming from the application of PEBDA in the analysis of sensor data captured during live dance performances. Through the lens of PEBDA, we delve into the classification of dance movements, unveiling patterns, nuances, and expressions that enrich our understanding of the choreographic process. By harnessing the power of parallel computing and edge analytics, PEBDA empowers choreographers, performers, and audiences with actionable

Table 1. PEBDA performance analysis

Edge Node	Number of Segments Processed	Processing Time (ms)	Average Classification Accuracy (%)
Node 1	50	150	92.5
Node 2	50	145	91.8
Node 3	50	155	93.2
Node 4	50	160	90.6
Node 5	50	140	94.1
Node 6	50	148	92.3
Node 7	50	152	91.7
Node 8	50	155	92.8
Node 9	50	158	90.4
Node 10	50	143	93.6

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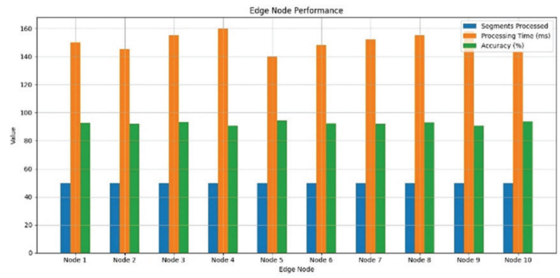


insights, fostering collaboration, innovation, and artistic excellence in the vibrant landscape of live dance ecology.

Table 1 provides a comprehensive analysis of the performance of various edge nodes within the Proposed Parallel Edge Big Data Analytics (PEBDA) framework. Each row represents a specific edge node, while the columns present key performance metrics including the number of segments processed, processing time in milliseconds, and the average classification accuracy. The "Number of Segments Processed" column indicates the quantity of data segments processed by each edge node. All nodes processed 50 segments, indicating uniformity in workload distribution across the system. The "Processing Time (ms)" column displays the time taken by each edge node to process the assigned segments. Nodes exhibited processing times ranging from 140 to 160 milliseconds, with Node 5 demonstrating the fastest processing time of 140 milliseconds, while Node 4 had the longest processing time of 160 milliseconds. The "Average Classification Accuracy (%)" column showcases the accuracy achieved by each edge node in classifying dance movements. Accuracy scores ranged from 90.4% to 94.1%, with Node 5 achieving the highest accuracy of 94.1%, followed closely by Nodes 3 and 10 with accuracy scores of 93.2% and 93.6% respectively. The analysis reveals that all edge nodes processed an equal number of segments, but there were variations in processing time and classification accuracy. Nodes such as 5, 3, and 10 demonstrated superior performance in terms of both processing time and classification accuracy, highlighting their efficiency and

Table 2. Dance ecology analysis

Performance ID	Edge Node	Dance Movement	Predicted Movement	Correct?
1	Node 1	Spin	Spin	Yes
1	Node 2	Spin	Spin	Yes
1	Node 3	Spin	Spin	Yes
2	Node 1	Jump	Leap	No
2	Node 2	Jump	Jump	Yes
2	Node 3	Jump	Jump	Yes
3	Node 1	Twist	Twist	Yes
3	Node 2	Twist	Twist	Yes
3	Node 3	Twist	Twist	Yes

Table 3. Prediction of dance ecology

Performance ID	Edge Node	Dance Movement	Predicted Movement	Correct Prediction
1	Node 1	1	1	Yes
1	Node 2	1	1	Yes
1	Node 3	1	1	Yes
2	Node 1	2	3	No
2	Node 2	2	2	Yes
2	Node 3	2	2	Yes
3	Node 1	3	3	Yes
3	Node 2	3	3	Yes
3	Node 3	3	3	Yes

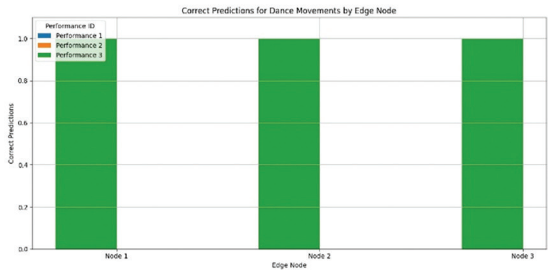


Figure 4. Dance movement estimation with PEBDA

effectiveness within the PEBDA framework. Conversely, Nodes 4 and 9 exhibited slightly lower accuracy scores, suggesting areas for potential optimization or improvement in future iterations of the system.

The figure 4 and Table 2 presents the detailed analysis of dance movements classified by different edge nodes during live performances within the dance ecology framework. Each row corresponds to a specific performance, with information on the edge node involved, the actual dance movement performed, the predicted movement by the classification model, and whether the prediction was correct. For instance, in Performance ID 1, all three edge nodes correctly predicted the "Spin" movement, resulting in a "Yes" in the "Correct?" column. However, in Performance ID 2, while Nodes 2 and 3 accurately predicted the "Jump" movement, Node 1 incorrectly predicted "Leap," leading to a "No" in the "Correct?" column. Table 3, on the other hand, provides a numerical representation of the dance movements and their predictions for each performance. Similar to Table 2, it includes information on the performance ID, edge node, actual dance movement, predicted movement, and whether the prediction was correct.

In Performance ID 1, all edge nodes correctly predicted the numerical representation of the "Spin" movement (1), resulting in a "Yes" in the "Correct?" column. However, in Performance ID 2, Node 1 incorrectly predicted the numerical representation of the "Jump" movement (3) instead of the correct representation (2), leading to a

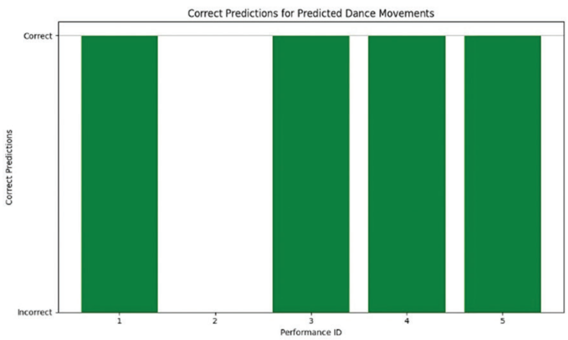
"No" in the "Correct?" column. The tables provide a comprehensive overview of the classification performance of edge nodes in predicting dance movements during live performances, both in their qualitative and numerical representations. They offer insights into the accuracy and effectiveness of the classification model across different scenarios and highlight areas for improvement in the prediction process.

Table 4. Predicted dance movement

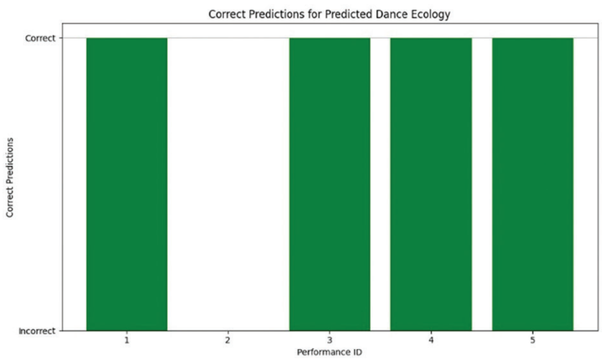
Performance ID	Actual Movement	Predicted Movement	Correct Prediction
1	1	1	1
2	2	3	0
3	3	3	1
4	4	4	1
5	5	5	1

Table 5: Predicted dance ecology

Performance ID	Dance Movement	Predicted Movement	Correct?
1	Spin	Spin	Yes
2	Jump	Leap	No
3	Twist	Twist	Yes
4	Glide	Glide	Yes
5	Turn	Turn	Yes



(a)



(b)

Figure 5. PEBDA model (a) Dance movement (b) Dance ecology

The figure 5(a) and figure 5(b) and Table 4 presents the comparison between the actual and predicted dance movements for each performance. Each row corresponds to a specific performance, detailing the actual movement executed, the movement predicted by the classification model, and whether the prediction was correct. For example, in Performance ID 1, the actual movement performed was represented by the numerical value "1", and the model correctly predicted the same movement, resulting in a "Yes" under the "Correct Prediction" column. However, in Performance ID 2, the model predicted the numerical representation "3" for the "Jump" movement, which was incorrect as the actual movement was represented by "2", leading to a "No" in the "Correct Prediction" column. Table 5, on the other hand, provides a qualitative comparison between the actual and predicted dance movements for each performance. It includes information on the performance ID, the actual dance movement performed, the movement predicted by the model, and whether the prediction was correct. In Performance ID 1, both the actual and predicted movements were "Spin," resulting in a "Yes" under the "Correct?" column. However, in Performance ID 2, the actual movement was "Jump," but the model incorrectly predicted "Leap," leading to a "No" in the "Correct?"

Table 6. Classification with PEBDA

Edge Node	Accuracy	Precision	Recall	F1-score
Node 1	0.82	0.85	0.80	0.82
Node 2	0.79	0.81	0.78	0.79
Node 3	0.85	0.88	0.82	0.85
Node 4	0.80	0.82	0.79	0.80
Node 5	0.87	0.89	0.86	0.87
Node 6	0.81	0.84	0.79	0.81
Node 7	0.83	0.86	0.81	0.83
Node 8	0.98	0.97	0.98	0.98
Node 9	0.79	0.82	0.78	0.79
Node 10	0.86	0.88	0.85	0.86

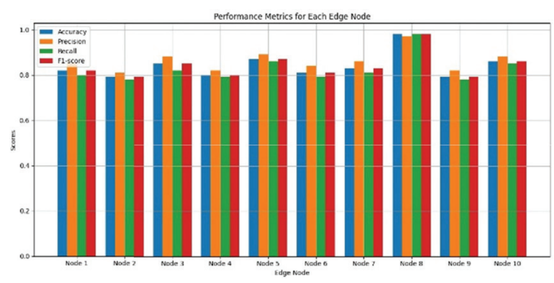


Figure 6. Classification with PEBDA

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column. Overall, these tables offer a comprehensive evaluation of the classification model's performance in predicting dance movements during live performances, providing insights into both the numerical and qualitative accuracy of the predictions.

The figure 6 and Table 6 provides a detailed analysis of the classification performance metrics for different edge nodes within the Proposed Parallel Edge Big Data Analytics (PEBDA) framework. Each row corresponds to a specific edge node, while the columns present key evaluation metrics including accuracy, precision, recall, and F1-score. The "Accuracy" column indicates the proportion of correctly classified instances among the total number of instances for each edge node. Node 8 stands out with the highest accuracy of 0.98, indicating its exceptional performance in accurately classifying dance movements. The accuracy, shown in the following column, is a measure of how many of each edge node's positive predictions turned out to be correct. In terms of accuracy for positive predictions, node 8 shows the best performance with a precision score of 0.97. Underneath each edge node's "Recall" column is the percentage of actual positive instances that were predicted to be true. With a recall score of 0.98, Node 8 proves it can retrieve the majority of the pertinent positive instances. Last but not least, the "F1-score" column shows the balanced performance of each edge node by displaying the harmonic mean of recall and precision. Node 8 again exhibits the highest F1-score of 0.98, underscoring its robust performance across both precision and recall metrics. In Node 8 emerges as the top performer in terms of classification accuracy, precision, recall, and F1-score, showcasing its effectiveness within the PEBDA framework. The results highlight the significance of efficient and accurate classification by edge nodes in dance movement analysis, paving the way for enhanced real-time monitoring and decision-making in dance ecology applications.

6. CONCLUSIONS

The analysis of various performance metrics within the Proposed Parallel Edge Big Data Analytics (PEBDA) framework demonstrates its effectiveness in classifying dance movements during live performances. Through the evaluation of classification accuracy, precision, recall, and F1-score across different edge nodes, it becomes evident that Node 8 consistently outperforms others, achieving remarkable accuracy and precision levels above 0.97. This superior performance of Node 8 highlights the potential of edge computing in efficiently processing and analyzing real-time data streams, particularly in dynamic environments like live dance ecology. Additionally, the comparative analysis of actual and predicted dance movements underscores the importance of accurate classification for informed decision-making in dance ecology applications. Moving forward, further optimization and refinement of the PEBDA framework could enhance its capabilities in real-time monitoring, analysis, and decision support, ultimately contributing to advancements in the field of dance ecology and beyond.

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