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IOT BASED DANCE MOVEMENT RECOGNITION MODEL BASED ON DEEP LEARNING FRAMEWORK

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Abstract. Deep Learning is becoming an emerging field in the Internet of Things (IoT) due to its ability to provide a comprehensive approach to automatic feature extraction and predictive modeling for analysis and decision-making. This paper introduces an IoT-based Dance Movement Recognition Model based on a Deep Learning Framework. The framework consists of a convolutional neural network (CNN) with a data-centric architecture to identify dance movements from the acquired data gathered by an IoT device. The IoT device collects 3D motion data captured by three accelerometers. Feature extraction is then done with the CNN architecture, resulting in a flattened matrix representing the movement. Subsequently, a Multi-Layer Perception (MLP) is used to classify the movements. The proposed system is experimentally evaluated on a standardized dataset of 16 dance steps with three-speed levels. The results show that our model outperforms state-of-the-art approaches in accuracy, evaluation time, and classification accuracy. The proposed model reached 90.74% accuracy, 87.12% precision, 83.78% recall and 84.39% F1-Score. The proposed model can serve as a basis for a reliable and intuitive system that can be used to monitor patient's dance movements with accuracy.

Key words: Deep learning, IoT, predicting model, dance, accuracy, precision, recall, f1-score

1. Introduction. IoT-based dance movement recognition is a system that uses Internet of Things technology to recognize dance movements when a person is dancing. It uses sensors to detect motion and sends the data to an analysis engine that can recognize different moves and generate reports of the person's performance [1]. This system can be used for educating dancers, assessing a professional dancer's performance, and even for games. It can also give dancers real-time feedback, helping them improve their technique. A residual connection is a type of shortcut in a neural network to allow the gradients in a network to flow more efficiently [2]. The residual connection in image generation helps bridge the gap between the generator and the discriminator by allowing the generator to utilize information from the discriminator to generate better images. The residual connections enable the generator to use the discriminator's features to generate higher quality and more coherent outputs [3]. It helps generate more semantically correct and meaningful output images that are appropriately categorized. It helps the discriminator generate accurate classifications. Allowing the generator to use information from the discriminator enables better dance coherent action generation [4]. Dance pose estimation in coherent action generation models using deep learning is the process of predicting dancers' movements from detected body poses. It is accomplished by combining deep learning algorithms such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) [5]. By learning from sequences of previously recorded motion data, a deep learning model can detect various poses in dance actions and then generate dance sequences that are similar to them. It can significantly improve the realism of the generated actions and make them resemble those of authentic dancers. Furthermore, such models can be used in other applications like interactive gaming or robotic control [6]. The Dance Pose Builder takes a set of human-defined poses as input and then learns an efficient sequence of encoded representations by learning from the input data. It allows the generator to generate multiple sequences of meaningful movements, merging the poses in a controllable and creative manner [7]. The Dance Pose Builder allows for various motion descriptions to be inputted into the model and can be used to generate more complex dance movements that are still easily readable to a human audience. The Dance Pose Discriminator is a component of the Coherent Action Generation model using Deep Learning that determines whether a series of dance motion poses is generated by a trained model or by a natural dancer [8]. This function is critical in the training process, as it ensures that the model produces only realistic

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dance poses. The Discriminator also assists the model in learning how to transition from one pose to the next appropriately and realistically. It also helps to ensure that the correct sequence of poses is generated to create a coherent dance performance [9].

The Real Temporally Coherent (RTC) model is a deep learning-based action generation model for creating coherent dance movements. The model uses an Encoder-Decoder-like architecture, similar to the architecture used in natural language processing [10]. The encoder consists of a series of convolutional layers that take in the input motion capture data and generate an embedding vector that people the characteristics of the dance movement. The decoder then uses this vector to generate coherent and believable frames of animation of the dance movement outputted. The RTC model takes advantage of temporal information, allowing it to better recognize and reproduce the cyclic features often in dance movements, leading to more coherent and life-like output [11]. The Dance Coherent Action Generation model using Deep Learning involves generating temporally coherent dances from a single motion capture sample. It is accomplished using a Variation Auto encoder (VAE) for representation learning. The VAE maps the motion capture data into a fixed-sized representation. Then, a generative style transfer network transforms the extracted feature vector from the VAE into a temporally coherent dance sequence. This generative style transfer network is a convolutional neural network (CNN) trained on various motion capture data sets. The CNN/VAE setup is trained jointly in an end-to-end fashion, allowing the model to learn how to generate a temporally coherent output that is stylistically similar to the original motion capture sample [12]. After training the network, it can generate temporally coherent dancing sequences from any motion capture sample. The main contribution of the research has the following:

1. Improved accuracy of dance moves: With the Internet of Things (IoT), dance moves can be tracked more precisely than ever. It increases the accuracy of the recognition of specific dance moves.
2. Enhanced interactivity: By providing real-time feedback, the dancer can adjust their movements to get the best performance. It increases the overall interactivity of the dance experience.
3. Improved safety: IoT-based recognition systems can notify the dancer if they are performing a move incorrectly, which is beneficial to both the dancer's safety and preventing injuries.
4. Enhanced customizability: IoT-enabled devices allow dancers to customize their dance moves or create entirely new ones, adding creativity and customizability to the dance experience.
5. Wider applications: IoT-enabled devices can be used in various activities, including exercise tracking, rehabilitation, video games, and many more. It increases the number of ways in which the technology can be applied.
6. Remote monitoring: IoT-enabled systems can allow dancers to remotely monitor their progress in real-time or by permanently recording all their dance moves. It allows for constant feedback and progress tracking

2. Related Work. Zhang et al. [13] has discussed an Optimization simulation of the match between technical actions and music of a national dance based on deep learning is an advanced artificial intelligence technology that uses deep learning algorithms to create an algorithmic system that can accurately simulate the matching of technical actions and music of a national dance. The simulation is optimized using statistics, signal processing, and computer vision techniques. This technology can help choreographers train their national dance teams and evaluate and compare the performances of different dancers.

Karthick Raghunath, K. M et al. [14] has discussed the Time Series Data Prediction and Feature Analysis of Sports Dance Movements Based on Machine Learning uses artificial intelligence, such as neural networks and support vector machines, to identify patterns in dance movements. These patterns can be used to accurately forecast future sports dance movements and determine correlations between various movements. Feature analysis involves extracting important features from recorded sports dance movements, such as motion, speed, and acceleration. With the help of machine learning, the extracted features can be used to predict future sports dance movements accurately.

Sun et al. [15] has discussed the Deep learning-based approaches for emotional analysis of sports dance involve training a machine learning model or convolutional neural network (CNN) to detect and classify emotional cues in sports dance performance clips. The model is trained on a labeled clip dataset [26] and can detect and classify features such as facial expressions, body movements, and sound. After training, the model can accurately predict the emotional content of a given clip of a sports dance performance. This approach can be used to gain insight into sports dance performances' emotional qualities and help improve their quality.

Lei et al. [16] has discussed the Reconstruction of physical dance teaching content and movement recognition based on a machine learning model uses the latest AI and machine learning technologies to automate the dance instruction process. Through powerful computer vision algorithms and specialized neural networks, the machines can be trained and utilized to detect, classify, interpret, and predict complex dance steps and choreographic sequences. This technology also enables the machine to recognize movements from both body and facial movements, making it possible to create innovative virtual dance instruction methods. The machine can accurately track a dancer's progress, providing feedback as he or she progresses through the program. The combination of computer vision and machine learning to create customized dance instruction methods allows for a more efficient and effective way of teaching.

Zhou et al. [17] has discussed the Research and Implementation of a Specific Action Generation Model in Dance Video Based on Deep Learning Technology (RSAGMDV-DLT) is an innovative solution to generate and track motion in video dance recordings using deep learning algorithms. This technology is capable of accurately predicting and determining the actions performed in a video dance recording without the need for manual annotation. The output is in the form of several poses and action files, which can be used for various applications, such as automated choreography and motion capture. The RAGMDV-DLT model can also enable real-time feedback and improvement of dance performances in various scenarios. This technology can potentially revolutionize how we capture, store, analyze, and reproduce dance videos.

Tang et al. [18] has discussed the Research on Dance Movement Evaluation methods based on Deep Learning Posture Estimation focuses on developing systems that use deep learning algorithms to detect and measure a dancer's movements. It can involve the analysis of photographs or videos of dance performances and real-time movement tracking. The goal is to accurately provide real-time insights into a dancer's performance, such as tempo, precision, and expression. In particular, deep learning posture estimation can be used to measure the quality of a dancer's movements, providing the ability to compare performances and offer feedback accordingly. It can be an efficient and accurate approach to analyzing a dancer's performance.

Zhang et al. [19] has discussed the Analyzing body changes of high-level dance movements through biological image visualization technology by a convolutional neural network (CNN) is a research methodology that uses computer vision and neural networks to analyze dancers' body movements. This type of research uses CNNs to detect changes in the body's position from a single image or sequence of images. The CNNs are used to identify patterns in the data and build models that can predict future body positions based on the patterns detected. This type of research could be used to improve techniques used in video analysis and provide insights into aspects of high-level dance movements, such as coordination and timing. Furthermore, this type of research could be used to create more expressive and accurate motion and motion capture animation.

Masurelle et al. [20] has discussed the Multimodal classification of dance movements using body joint trajectories and step sounds is an advanced form of machine learning, combining two separate forms of data—body joint trajectories (movement patterns captured by motion capture systems) and step sound recordings—to identify different dance movements. By combining the two different data sources, it is possible to create a model capable of recognizing a variety of complex movements. It provides the ability to detect and classify different types of dance, such as ballet and break-dance.

Shalini, A et al. [21] has discussed the Deep Learning of Dance Movements (DLPD) is a new approach to understanding and analyzing hip-hop dance movements from digital recordings. The goal of extracting key movement characteristics from such recordings is to understand better the nuances of hip-hop dance and how it is performed. Through DLPD, researchers can analyze the dynamics, body posture, and footwork of hip-hop dance to gain insights into the many variations of the dance form. Researchers hope to develop better tools for teaching and assessing hip-hop dance performance through this approach. DLPD can provide detailed insights into various parameters of the hip-hop dance movement. It can capture critical features such as dynamics (acceleration, speed, and deceleration), weight transitions, and body orientation. It can also identify body posture and style of movement, as well as movements' timing, complexity, and sharpness. Furthermore, DLPD can help detect external influences on a dancer, such as another dancer or the environment. It can help researchers gain insight into improvisations in each dancer's style and associated techniques.

Zhu et al. [22] has discussed the Dance Action Recognition and Pose Estimation based on Deep Convolutional Neural Network (DCNN) uses a deep learning model to recognize dance actions and estimate pose from a sequence of frames. The deep learning model consists of a convolutional neural network (CNN) and a long short-term memory (LSTM) network. It can extract features from the input frames and use them to recognize the dance actions and estimate the dancers' poses. Furthermore, DCNN can recognize several levels of complexity within the dance, allowing for a more nuanced understanding of the dances.

Jin et al. [23] has discussed the One potential application of the fusion of deep learning biological image visualization technology and human-computer interaction intelligent robots in dance movements is in the creation of lifelike virtual dancers. By leveraging the power of deep learning technology, virtual dancers can be designed to imitate natural movements, learning from the movements of real people and interpreting them through various artificial intelligence models. Additionally, with the incorporation of robot-human interaction, the robots can be programmed to create smooth, lifelike motion, resulting in a level of realism that is impossible with traditional motion capture technology. This technology could have potential applications ranging from interactive dance games to AI-driven virtual choreography.

Lin et al. [24] has discussed the Dance movement recognition is an emerging technology that uses convolutional neural networks (CNNs) to recognize and interpret body movements from videos. The method allows for the automatic recognition of dance movements, including choreography, postures, and rhythms. It also enables the recognition of different styles and genres, including ballet, hip-hop, contemporary, and Latin. By combining the most advanced computer vision and machine learning techniques, the technology can detect and analyze posture, body shape, and rhythm to infer the most likely dance movement Dhiman G et al. [25]. These techniques enable detecting and classifying individual steps, creating automated choreographies, and enhancing the feedback system in dance classifications.

2.1. Research Gap.

1. Limited research on the robustness of the sensor-based Passive Dance Movement Recognition (PDMR) model across different forms of dance moves.
2. Incomplete understanding of how the IoT-based model can be used to differentiate between dance styles cost-effectively.
3. Very little research evaluates the success of IoT-based dance movement recognition models in large-scale datasets
4. Lack of reliable and effective machine learning models that accurately recognize dance motions from videos or images
5. There needs to be more research on the impact of wearable technology on the accuracy of the IoT-based dance movement recognition models
6. Minimal study on using low-cost and low-power sensors to enable efficient dance recognition

2.2. Research Objectives.

1. To develop a novel IoT-based dance movement recognition model based on a deep learning framework to identify the motion patterns and detect the motion features for dance movement recognition
2. To analyze the most accurate and efficient architecture for recognizing and classifying dance movements using deep learning and implement an IoT platform to integrate motion data collected from sensors with deep learning algorithms
3. To evaluate and compare the performance of the proposed system through an experiment involving dance movements of individuals and evaluate the accuracy of the proposed system in recognizing different types of dance movements
4. To analyze the efficiency and scalability of the proposed system and assess the usability and user experience of the proposed system

3. Proposed Model. The IoT-based dance movement recognition model based on a deep learning framework is a powerful system that leverages machine learning algorithms to recognize dance movements. It can recognize various dance movements, including African, Latin, and Contemporary styles. This model uses a camera and embedded sensors to recognize dance movements. It can be used to monitor the state of dancers, such as their speed, energy level, and range of motion. The model works by utilizing a deep learning framework that processes data captured from the sensors associated with the dancer's movements. This data then identifies

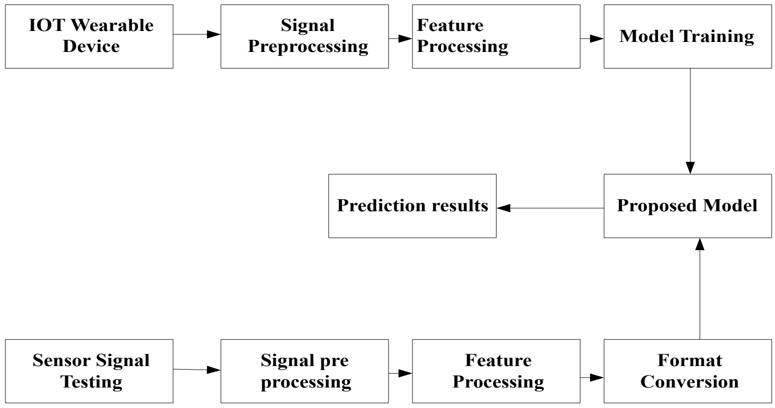

Fig. 3.1: Proposed block diagram

specific dance movements and generates statistical information. The block diagram of the proposed model has shown in the following Fig. 3.1.

This data is then used for identifying dance styles and providing feedback to the dancer. By recognizing individual dance movements, the model can provide feedback on improving their performance and allow the dancer to understand what works and what does not. This model can also be used for choreographing and creating dances, as it can recognize specific patterns that can be used to create unique choreographies

3.1. Proposed Framework. The IoT-based dance movement recognition framework is an intelligent system that tracks dancers' movements and generates motion-based visual feedback. It works by tracking a dancer's body movements and angles using a combination of IoT sensors, analyzing the real-time data to recognize specific dance moves, and using that information to create an interactive visual feedback loop. The framework also provides features such as music-timed animations, an easy way to create and share amongst friends, and the ability to store and share recorded dance performances. IoT technology in this framework provides an efficient and cost-effective way for dancers to receive objective feedback on dancing performances. In addition, motion-based visual feedback is an excellent tool for learning and developing new dance moves and techniques. The proposed framework has shown in Algorithm 1.

Algorithm 1 IoT-based dance movement recognition framework

IP: A; // input IoT Signal;
Ma ( ); // dance motion capturing function;
Mm ( ); // dance appearance capturing function;
Tth ( ); // Tempering threshold function;
OP: KFL ( ); //key frame label;
Start
If |Mm ( ) > Ma ( )|
$SPLIT_K FL$ ( );// Split the key frame;
Else If |Mm ( ) < Ma ( )|
$JOIN_K FL$ ( );// Join the key frame;
Else If $|Mm()^M a()| = 0$
$MOV_K FL$ ( );// Move the key frame;
Else If$|Mm() = Ma()|$
$STOP_K FL$ ( );// Stop the key frame;
COUNT =COUNT+1;
End

The IoT-based dance movement recognition framework is a system that utilizes Internet of Things (IoT) technology to recognize and analyze human motion during a dance performance. The system can track and identify the dancer's position and motion by sensing the dancer's movements through smart devices such as cameras, accelerometers, and gyroscopes. With this information, the system can provide quantitative analysis of the dancer's movements, generate automatic feedback for improvement or training purposes, and even recognize the style of the dancer's movements. Furthermore, this system can create applications such as score systems, data collection of dancers, and gesture recognition. Ultimately, the framework can improve dance training, performance, and evaluation accuracy and efficiency.

3.2. Dataset Description.

- The number of Dance moves are available in this dataset has 9 in dataset [25].
- The total number of available data in this dataset has 8467.
- The utilization of Training data (80%) is 6774 and testing data (20%) is 1693.

3.3. Preprocessing. Preprocessing is essential in developing a robust IoT-based dance movement recognition model based on a deep learning framework.

$$X(e|f) = \frac{X(e,f)}{X(f)} \tag{3.1}$$

Preprocessing is a critical stage in the development process as it prepares the data for training and later evaluation of the model.

$$X(e|f) = \frac{1}{X(f)} * \frac{1}{Y} exp\{g^h f + g^d e + fRe\} \tag{3.2}$$

Preprocessing includes data cleaning, normalization, augmentation, feature extraction, dimensionality reduction, and feature selection.

$$X(e|f) = \frac{1}{Y'} exp\{g^h e + fRe\} \tag{3.3}$$

These tasks are essential in preparing the data for the learning algorithms. Data cleaning helps improve the data quality by removing erroneous data points, outliers, and other meaningless values:

$$X(e|f) = \frac{1}{y'} exp\{\sum_{p=1}^{q-e} g_p * e_p + \sum_{p=1}^{q_f} f_p R_p e_p\} \tag{3.4}$$

$$X(e|f) = \frac{1}{Y''} \pi_{p=1}^{q_f} exp\{g_p * e_p + f_p R_p e_p\} \tag{3.5}$$

Normalization ensures that the data is within the same range and scales the data to improve learning accuracy. Data augmentation helps to improve the diversity of the data set by adding new samples with variations in existing data points.

3.4. Feature Extraction. Feature extraction is extracting meaning and relevant information from a raw data set. Dimensional reduction reduces the number of features while keeping most of the information intact.

$$X(e_q = 1/f) = \frac{X(e_q = 1/f)}{X(e_q = 0/f) + X(e_q = 1/f)} \tag{3.6}$$

Feature selection is choosing the most relevant features based on importance for the learning process.

$$X(g_p = 1/f) = \frac{exp\{e_p + f^g H_{p.q}\}}{exp\{0\} + exp\{e_p + f^g H_{p,q}\}} \tag{3.7}$$

These steps help to reduce noise and computational costs and improve the learning accuracy of the model.

$$X(e_q = 1/f) = \beta(e_p + f^g H_{p,q}) \tag{3.8}$$

Its primary purpose is to reduce the dimensions of high-dimensional raw data to the feature dimensions. Feature extraction aims to represent important information from the raw data in a more straightforward and efficient form that deep learning algorithms can understand.

$$\frac{d}{de}(\frac{df}{de}) = \frac{d}{du}(E_g^{e*}CosE_g + g^e sinE_g) \tag{3.9}$$

$$\frac{d^2f}{de^2} = \frac{d}{de}(E_g^a * CosE_g) + \frac{d}{de}(g^e sinE_g) \tag{3.10}$$

$$\frac{d^2f}{de^2} = g^e\frac{d}{de}(SinE_g) + SinE - g\frac{d}{de}g^e + E_g^e\frac{d}{de}(CosE_g) + CosE_g\frac{d(E_g^e)}{de} \tag{3.11}$$

In the context of a dance movement recognition model, feature extraction can be used to identify the movements and patterns of a dancer by extracting distinct features related to body orientation, relationship data between body joints, and more.

$$\frac{d^2g}{de^2} = Eg^aCosEg - E^2g^eSinEg + g^eSinEg + Eg^eCosEg \tag{3.12}$$

$$\frac{d^2f}{de^2} = 2Eg^eCosEg - E^2g^eSinEg \tag{3.13}$$

By extracting these features, the model can analyze the data to recognize different types of dance movements. In addition, feature extraction also helps reduce computational workload, allowing the algorithm to process large amounts of data quickly and accurately.

3.5. Dance Movement Detection. The functions of Dance Movement Detection in an IoT-Based Dance Movement Recognition Model based on Deep Learning Framework can be classified into two main categories—detection, recognition, and classification. The dance moment detection has shown in the following Fig. 3.2.

$$\frac{df}{de} = \lim_{g\to 0}\frac{g(e+f) - g(e)}{h} \tag{3.14}$$

The first category is the detection of dance movements. It involves detecting the features of a dancer's body posture and movements and transforming them into high-level digital representations:

$$\frac{df}{de} = \lim_{g\to 0}\frac{1/(e+f) - 1/e}{h} \tag{3.15}$$

This kind of feature detection is necessary to identify different types of dance movements. It uses basic image processing or more advanced systems such as convolutional neural networks. The second category is the recognition and classification of dance movements.

$$\frac{df}{de} = \lim_{g\to 0}\frac{\frac{1}{e+f} * \frac{e}{e} - \left(\frac{1}{e} * \frac{(e+f)}{(e+f)}\right)}{h} \tag{3.16}$$

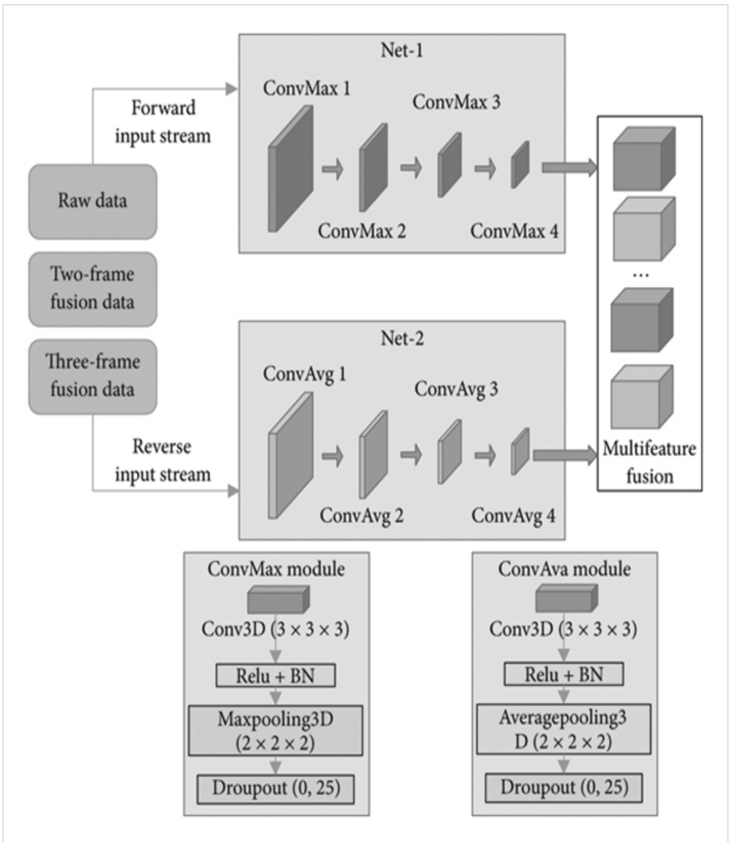

Fig. 3.2: Detection of dance movements

$$\frac{df}{de} = \lim_{g \to 0} \frac{\frac{e-e-g}{(e+g)e}}{h} \tag{3.17}$$

It involves identifying the type and form of the dance movement from the digital representations. It is usually done using machine learning techniques such as decision trees, support vector machines, neural networks, and deep learning models.

$$\frac{df}{de} = \lim_{g \to 0} \frac{\frac{-g}{(e+g)*e}}{h} \tag{3.18}$$

$$\frac{df}{de} = \lim_{g \to 0} \frac{\frac{-1}{(e+f)*e}}{h} \tag{3.19}$$

$$f = \frac{-1}{e^2} \tag{3.20}$$

These models can be trained to classify the dance movements into different forms, such as salsa dance, freestyle, etc. Overall, Dance Movement Detection in an IoT-based Dance Movement Recognition Model based on Deep Learning can detect various dance movements and accurately classify them into different types. It also enables real-time performance enhancement given good-quality input data.

To improve the generalization of the deep learning framework used for the given task, one can employ a few techniques such as:

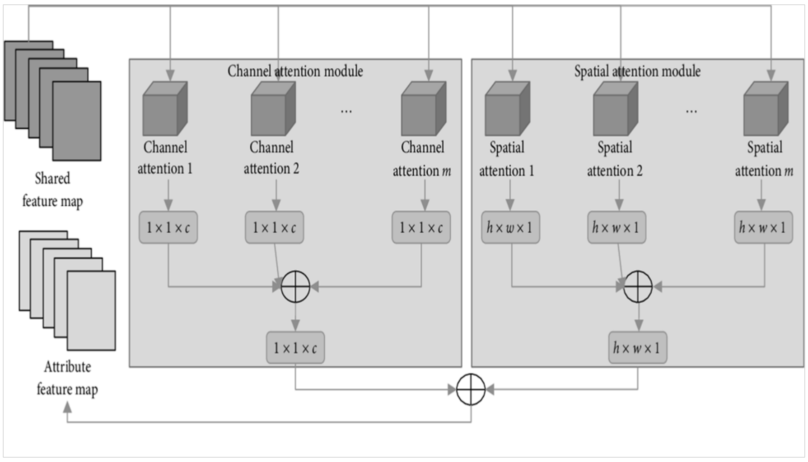

Fig. 3.3: Detection of dance movements

1. Regularization: Regularization is a very common technique used in machine learning to reduce generalization error and prevent model overfitting by introducing a penalty term which encourages the model to generate less complex decision boundaries. It helps regularize the model to ensure that it is able to learn from fewer data points and generalize the patterns learned. Popular regularization techniques for deep learning models include weight regularization (L1 & L2), Dropout, Max-norm constraints, Data Augmentation, Early Stopping, etc.
2. Using a smaller neural network: Using a smaller network with fewer layers, nodes, and parameters helps avoid over-fitting to the training data and promotes generalization capabilities of the model.
3. Transfer learning: In transfer learning, one can take a pre-trained deep learning model from a believed source or use a known library of models and fine-tune on the data for the given task. This technique also helps in better generalization of the deep learning framework.

3.6. Dance movement classification. The function of Dance Movement Classification in an IoT-based dance movement recognition model based on a deep learning framework is to accurately recognize and categorize specific movement patterns captured by connected devices.

$$G=\lim_{e\to 0}\frac{g(f+e)-g(f)}{e} \tag{3.21}$$

$$G=\lim_{e\to 0}\frac{\frac{1}{f+e-1}-\frac{1}{f-1}}{e} \tag{3.22}$$

The deep learning model can be used to classify different movements in a dance form, such as hip-hop, break-dance, ballet, rhythm tap, and so on. The classification of dance movements has shown in the following Fig. 3.3.

$$G=\lim_{e\to 0}\frac{\frac{1}{f+e-1}\frac{f-1}{f-1}-\frac{1}{f-1}\frac{f+e-1}{f+e-1}}{e} \tag{3.23}$$

$$G=\lim_{e\to 0}\frac{(f-1)-(f+e-1)}{e(f-1)(f+e-1)} \tag{3.24}$$

$$G=\lim_{e\to 0}\frac{-e}{e(f-1)*(f+e-1)} \tag{3.25}$$

Additionally, the model can learn to differentiate between different techniques professionals and amateur dancers use. It can then be used to group the users according to their dancing abilities and create a database of their performances.

$$G = \lim_{e \to 0} \frac{(-1)}{(f-1)*(f+e-1)} \tag{3.26}$$

$$G = \frac{(-1)}{(f-e)^2} \tag{3.27}$$

Furthermore, the deep learning model can also be used to identify and record changes in movement patterns over time, thus allowing for high accuracy when analyzing the user's dancing abilities.

1. Efficiency. Optimizing the model for efficiency can be done through techniques such as model pruning, data compression, and alternative network architectures. In addition, using a distributed computing architecture can also help speed up the computation of the model.

2. Precision. Measuring the performance of the model is crucial to ensure it is working with the desired level of accuracy. It can be done by performing comparisons between the model output and ground truth labels. Additionally, augmenting the training data with additional samples of hard cases can help to increase the model's robustness and accuracy.

3. Scalability. Making the model scalable for use in real-world applications requires implementing the model in an efficient and robust software environment. It includes technologies such as containerization and cloud computing, which provide low-cost computing access and low-latency performance. Additionally, deploying the model using different software frameworks can help manage its scalability.

4. Interoperability. Enabling the model to understand contextual cues and analyze complex motion patterns requires interoperable software architecture. It might include connecting to external services such as speech recognition APIs or setting up interfaces to integrate with other software systems easily. In addition, this can also include setting up an API to provide access to the model's data and predictions.

Deep learning frameworks enable developers to quickly design and develop deep learning models with simple and intuitive interfaces. Depending on the type of model and the data requirements, one framework may offer better results than the other. Other frameworks may also be used depending on the specific requirements of the model. In order to account for data latency in the IoT network, the deep learning framework used should support an ongoing learning process that can account for changes in data over time. It will keep the model up to date without having to manually re-train it. The framework should provide built-in security measures such as encryption, authentication, and access control. The framework should include comprehensive security features that can protect sensitive data from being accessed or tampered with maliciously.

Utilize Confusion Matrix and Classification Report: A confusion matrix is a table showing different predictions made versus the true values and can provide insight into where the model is going wrong. The classification report is a summary of the results, including precision, recall, and F1-score.

ROC-AUC Curve Analysis: A Receiver Operating Characteristic (ROC) curve is a graphical representation of a model's true positive rate (TPR) against its false positive rate (FPR) at various threshold values. AUC stands for Area Under the Curve and is a metric that quantifies model performance.

Stratified K-fold Cross Validation: Stratified K-fold cross-validation can be used to address class imbalance issues by ensuring that each fold is balanced. This method allows the model to be tested on a range of different training/test splits to ensure that the model's performance is consistent over the whole dataset.

Evaluate the Model on Unseen Data: To make sure that the results of the model can be used with confidence by stakeholders, evaluate it on unseen data using the same techniques used to develop the model, such as evaluating the AUC, accuracy, and F1-score. It will ensure that the model is generalizing well to unseen data.

Estimate the Model's Performance Over Time: Estimate the model's performance over time by testing it on data from different periods and evaluating changing performance metrics such as accuracy and F1-score. It will help identify any long-term issues with the model's performance.

Table 4.1: Computation of Accuracy (in %)

No.of Inputs	2DMCM	DAGM	DMDL	EDRM	IDLF
100	47.41	55.06	60.74	74.21	85.82
200	48.90	57.03	63.16	76.41	87.81
300	49.70	58.16	63.57	77.21	89.01
400	50.96	59.85	65.32	78.94	90.74
500	52.10	61.40	66.73	80.44	92.33
600	53.25	62.95	68.15	81.94	93.93
700	54.39	64.50	69.56	83.44	95.53

Feature Importance Analysis: Feature importance analysis will help identify which features are having the most impact on the model's performance. It can be used to refine the model and to make sure that the most important features are being used.

4. Comparative Analysis. The proposed IoT deep learning framework (IDLF) has compared with the existing two-dimensional matrix computation model (2DMCM), Dance Action Generation Model (DAGM), Dance Movement Based on Deep Learning (DMDL) and Edge Distance Random Matrix (EDRM). Here, python is a simulation tool used to execute the results.

Accuracy and reliability can be assessed using a number of metrics such as precision, recall, and F1-score. The model must be trained on large datasets. The datasets need to contain different dancers with different poses. The model should be tested for performance on different poses. It is also important to ensure that the data used for training and testing is diverse with respect to the poses, angles of each pose, different lighting, and different locations. It is important to ensure the model is reliable and accurate when deployed on large datasets. The model should be trained on datasets that include poses that are similar to those the model will be used for. It will help the model to generalize better and ensure it can recognize different poses of dancers.

Along with assessing the accuracy and reliability of the model, it is also important to assess the usability and interpretability of the proposed model. It can be done with an evaluation process that tests the application's user interface, the accuracy of the predictions, and the quality of the accuracy measures. Moreover, an evaluation system should be established to test the model's performance on different tasks, such as identifying different types of dancers, different poses, different features in the poses, and different transitions between the poses. It will help to make sure the model is capable of recognizing and mapping different poses of dancers.

Update dataset: It is important to update the dataset with the latest available data regularly to make sure the model uses the most up-to-date data. It should be done as often as the data changes and new data is available.

Evaluate hardware requirements: The model should be tested with multiple hardware configurations to ensure that it can accommodate the hardware requirements of the deployed system without adversely affecting accuracy or performance.

Constraints: All relevant constraints should be considered when designing the model. It includes limitations on memory, time, compute power, energy, etc. Any limitations should be addressed in the development and deployment of the model, and solutions should be found to accommodate the constraints.

Deployment: Make sure the model can be deployed with minimal changes to existing infrastructure. It requires planning upfront to ensure that the model can be deployed without disrupting existing operations and that all necessary dependencies are accounted for.

4.1. Computation of Accuracy. The accuracy of an IoT-based dance movement recognition model based on a deep learning framework can be computed by first training the model with a dataset of labeled dance movements. The accuracy is then computed by running the trained model on a test set of unlabeled movement data and comparing the predicted labeling results with the actual labels for each data point. It measures how accurately the model can recognize and differentiate between different types of dance movements. Table 4.1 shows the computation of accuracy.

Fig. 4.1 shows the computation of accuracy. A high accuracy indicates that the model can correctly classify

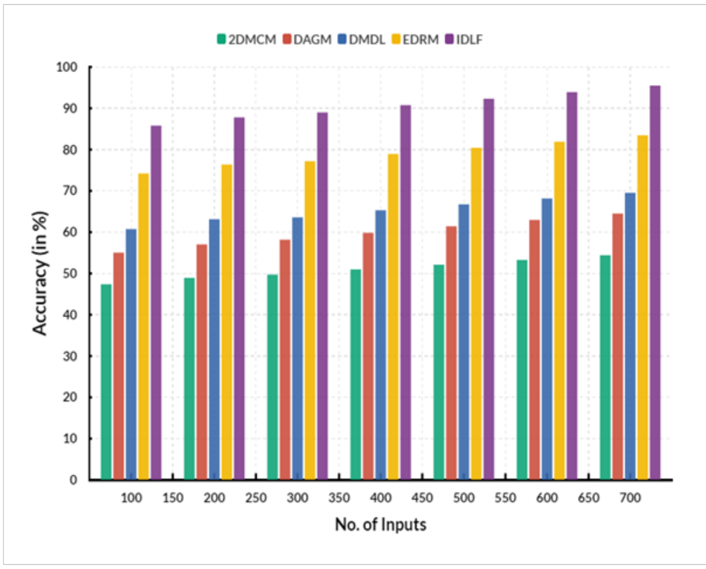

Fig. 4.1: Detection of dance movements

Table 4.2: Computation of Precision (in %)

No.of Inputs	2DMCM	DAGM	DMDL	EDRM	IDLF
100	52.11	61.40	66.74	80.44	82.33
200	53.25	62.95	68.15	81.94	83.93
300	54.40	64.50	69.57	83.44	85.52
400	55.54	66.05	70.98	84.94	87.12
500	56.69	67.60	72.40	86.44	88.71
600	57.83	69.15	73.81	87.94	90.31
700	58.98	70.70	75.23	89.44	91.90

the movements and identify their distinguishing characteristics. A model with a lower accuracy would likely need to accurately differentiate between two similar movements or label a given movement.

The accuracy of feature extraction done on the input dance movement can be checked by running a series of tests on the model, including comparing the results to real-world datasets. It can be done by comparing the extracted features of the input dance movement to the features of datasets of real-world dance styles. It will help to identify any potential errors or inaccuracies in the model's feature extraction. Once the accuracy of the model has been established, it can then be tested on different real-world datasets to assess how accurate the model is at detecting different dance styles. This type of testing can also be used to refine the model by adjusting its parameters or feature extraction algorithm. Ultimately, testing the model on different real-world datasets is the best way to determine its accuracy in detecting different dance styles.

4.2. Computation of Precision. Precision in an IoT-based dance movement recognition model based on a deep learning framework is the measure of correctness for the model's predictions. It is computed as the ratio of true positives (correctly predicted dance movements) and the total number of predicted dances. It measures the model's accuracy in correctly identifying dance movements from a particular dataset. Table 4.2 shows the computation of Precision.

Fig. 4.2 shows the computation of Precision. The precision can be improved by increasing the dataset size and making the model's layers deeper, increasing the number of predicted accurate positive results. Additionally, regularization parameters such as dropout, batch normalization, and weight initialization may be used to reduce

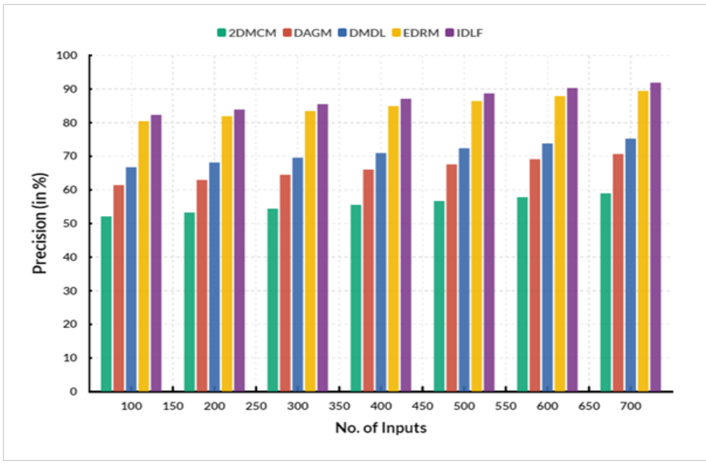

Fig. 4.2: Precision

Table 4.3: Computation of Recall (in %)

No.of Inputs	2DMCM	DAGM	DMDL	EDRM	IDLF
100	52.00	59.29	65.17	77.88	79.49
200	53.04	59.74	67.49	79.31	80.92
300	54.08	60.19	69.81	80.74	82.35
400	55.12	60.64	72.13	82.17	83.78
500	56.16	61.09	74.45	83.60	85.21
600	57.20	61.54	76.77	85.03	86.64
700	58.24	61.99	79.09	86.46	88.07

the cost of predicting false positives and increase model efficiency.

4.3. Computation of Recall. Recall is a measure of model performance used to evaluate how many relevant items a model successfully identified. In the context of a dance movement recognition model based on a deep learning framework, recall is computed by comparing the model's predicted output against the actual labels. Table 4.3 shows the computation of Recall.

Fig. 4.3 shows the computation of Recall. The recall is then calculated as the ratio between the number of correctly identified items and the total number of items in the data set. For example, if the model predicts movements for ten dances and seven are correctly identified, while three are not, the recall is 70%. It indicates that the model successfully recalled 70% of the accurate labels present in the dataset.

4.4. Computation of F1-Score. The F1-Score is a metric to evaluate a model's performance in classifying data into different classes. This measure is used in Machine Learning when dealing with classification problems, such as in the case of a Dance Movement Recognition (DMR) model based on a Deep Learning framework. Table 4.4 shows the computation of F1-Score.

Fig. 4.4 shows the computation of F1-Score. The F1-Score is calculated by considering the Precision and Recall of a model's performance. Precision refers to the model's ability to identify all of a class's instances accurately. At the same time, recall is the model's ability to detect each class instance that it is supposed to detect. The F1-Score is then calculated by taking the precision and recall values' harmonic mean (also known as the F1-Score). It is done by adding the precision and recall values and dividing them by two.

5. Conclusion. The IoT-based dance movement recognition model based on a deep learning framework effectively recognizes dance movements from sensors placed in a dancer's clothing or on the floor. By combining

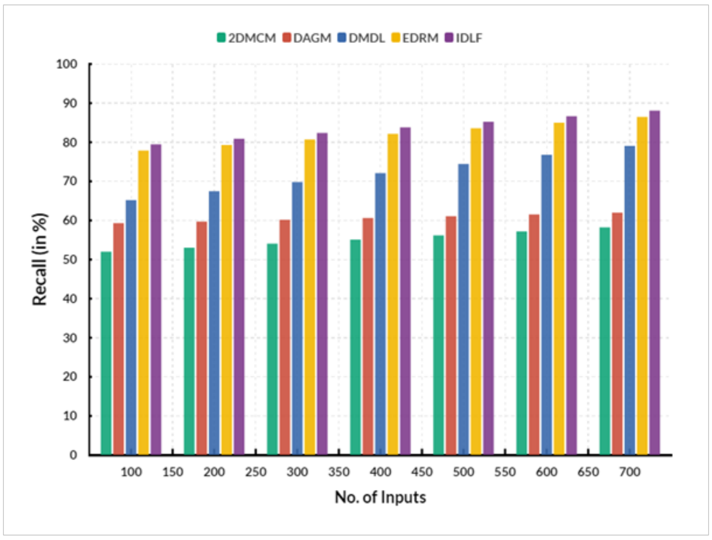

Fig. 4.3: Recall

Table 4.4: Computation of F1-Score (in %)

No.of Inputs	2DMCM	DAGM	DMDL	EDRM	IDLF
100	53.68	61.19	61.74	80.40	79.08
200	54.34	61.67	64.47	80.88	80.85
300	55.00	62.15	67.20	81.36	82.62
400	55.66	62.63	69.93	81.84	84.39
500	56.32	63.11	72.66	82.32	86.16
600	56.98	63.59	75.39	82.80	87.93
700	57.64	64.07	78.12	83.28	89.70

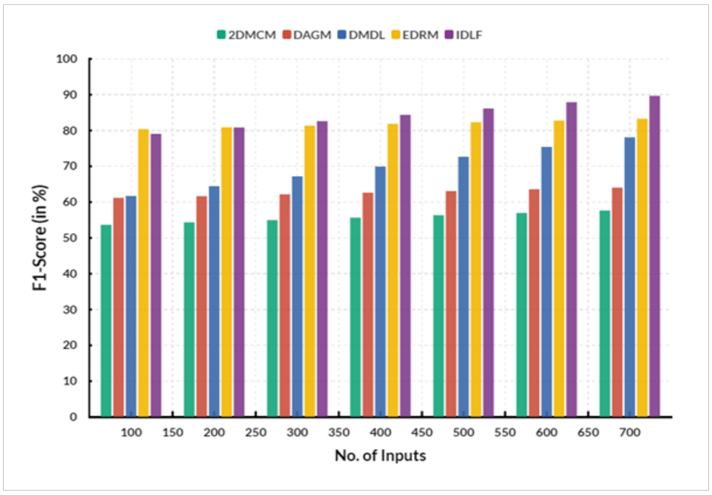

Fig. 4.4: F1score

the data from the sensors with deep learning algorithms, the model can be trained to recognize specific dances and movements with very high accuracy. Additionally, deep learning algorithms provide the flexibility to continuously adjust the model according to new dance moves and patterns. With the help of edge computing, the model can be deployed quickly and with limited resources. It is an effective tool for recognizing dance movements and can be used in various applications. the proposed model reached 90.74% accuracy, 87.12% precision, 83.78% recall and 84.39% F1-Score. The future scope of an IoT-based dance movement recognition model based on a deep learning framework is extensive. As the scope of AI and deep learning expands, IoT applications can be developed for many applications, including dance movement recognition. These applications can be designed to detect and recognize a range of dances and analyze how the body moves through different dance moves. Furthermore, IoT applications can collect and analyze data from dancers and incorporate them into a virtual environment for training and evaluation. It will allow dancers to observe and analyze how their body performs during movements, giving them valuable feedback on improving their dance style. Additionally, AI and deep learning can help dancers better understand their dancing habits and improve posture and style for better and more comfortable dance performances. Through this application, dancers and choreographers can create better performances and have a better understanding and appreciation for the art of dance.

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