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ORIGINAL RESEARCH

Entropy-aware ambient IoT analytics on humanized music information fusion

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Abstract

Musical information fusion in the era of Internet is participatory multi-sensor based heterogeneous musical data recognition and computing. Participatory devices enhance the progression of intelligent multimedia data fusion and analytics in the participated edge computing devices in the context of ambient Internet of Things. Sensed data streams coming from multi-sensors encounter the conventional methodologies for data analytics and are further transmitted to emerging big data archetype. The proposed contribution analyses, validates and evaluates a set of qualitative music data collected from wearable sound sensors. The authors present system architecture with three committed layers of participated devices for music fusion in the Internet of Things environment. Besides, an analytical case study on music fusion challenges is discussed along with the elucidation of their unique features in terms of Big data V-Scheme, followed by the demonstration of edge-cloud computing paradigm with deliberate evaluations. In this work, the system requirements in terms of data transmission latency and relevant power dissipation are visualized. The information and proposed system entropy of stochastic source of music data are evaluated in order to measure system efficiency and stability for performing multimedia communication. Quantitative evaluations are studied for comparison of heterogeneous system architectures in terms of system entropy that illustrate significant improvement in music fusion efficiency upon employing the proposed system archetype.

Keywords Internet of Things · Big data · Edge and cloud computing · Entropy · Latency · Power dissipation · Efficiency · Music fusion

1 Introduction

Multi-modal characteristics of multimedia information provide indispensable requirement in information fusion for data analytics, data tagging, recognition and retrieval (Khaleghi et al. 2013). In the context of music Information, fusion has a prodigious impression on activities like musical data retrieval and recognition (Roy et al. 2017). Information fusion is the well-established domain in technological researches and advancements for the past few decades although a hypothetical framework for defining humanized information fusion systems is still limited due to the existence of enormous data volume. Big data analytics (Ramírez-Gallego et al. 2018; García-Gil et al. 2018) has accomplished to be the thrust research area for in-depth analysis of the massive volume of sensed data, information processing and computing (Jararweh et al. 2015). The sensor devices sense the information from several sources of data. The smart devices enable data processing within the systems and transmit the processed information to the cloud-storage for providing services to the end-users (Al-Osta et al. 2018). Due to several limitations of the conventional cloud computing paradigm in terms of incentives, bandwidth availability, downtime, and control, the edge computing paradigm has been projected. In this paradigm, the edge devices lessen

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data transmission latency (Mukherjee et al. 2016) and utilize the available bandwidths optimally. The computational platforms are provided by substantial edge devices where the information processing and local analytics are performed on the sensor data. The processed data are thereafter sent to the cloud collectively for providing services to the end-users and decision-making (Khaleghi et al. 2013; Alamri et al. 2013). In the era of the Internet of Things, edge computing devices can be supportive towards data analytics (Gandomi and Haider 2015) such as user data analysis, data mining and warehousing (Wu et al. 2014). The IoT devices in the mobile edge computing scenario execute computation and abbreviate data volume prior to transmitting information to the cloud data centre. IoT analytics is an application platform for data analysis and event of actions to isolate meaningful data from a large data volume produced by connected IoT devices. These data are typically unstructured that causes difficulties in analysing traditional methods of data analytics. Ambient IoT analytics filters, transmutes, and augments IoT data before accumulating them in the time-series edge data store for computational tasks. IoT data integration and multi-sensor data fusion are the biggest challenges to IoT development which rely on ambient IoT analytics. Information fusion is the procedure for the integration of multiple data to harvest more effective, reliable, precise and beneficial information than the provided individual information within an explicit system. Music information fusion is the coalition of different musical genres in order to enhance the attention of music listeners. In IoT-aware musical data analytics, sound information sense using sound-sensing devices which frequently record unbiased noisy sound processes.

Therefore, designing a significant rather efficient information fusion system architecture is required to measure the level of performance and achieve an optimum outcome in terms of data processing latency, energy, power, entropy and so on. In this article, a comprehensive design and implementation of entropy-aware humanized music information fusion architecture for quality music composition in ambient IoT environment is presented. Here, a system with embedded, context-aware, personalized, adaptive and anticipatory attributes is depicted.

1.1 Motivation

Multi-sensor information fusion is a paradigm that assimilates signal processing, multimedia information systems, ambient intelligence, statistical analysis, and humanized computing altogether (Khaleghi et al. 2013). Through data analytics, the aforesaid paradigm can fuse the sensor data in diverse states and geo-spatial locations. It removes redundancy from multiple sensor information, condenses system uncertainty and articulates insightful explanation of the proposed system (Amoretti et al. 2013). Multimedia information from ubiquitous IoT devices is characteristically fragmented, unstructured, and often unlabelled. For renovating unstructured and fragmented data content to familiar systems, media-specific knowledge is required for demonstrating and computing multimedia data as well as their connotation at the semantic level. Having been motivated by the challenges of data integration and multi-sensor data fusion with reference to IoT, the authors have presented a comprehensive case-study for entropy-aware IoT analytics for humanized music information fusion in the present article. Music fusion depends on the extensive community and heterogeneous music sensing of at least two or more different genres and combining them into listener's preferences. Musical information sensed by the physical sensors and its computing in the cloud is an expensive job (Elmore et al. 2014). Intermediate edge devices between physical sensors and cloud tiers deliver an energy-efficient (Roy et al. 2018) and entropy-aware (Gray 2011) schema for service virtualization (Venticinque and Amato 2018) where edge computing devices show obtainable remote location computing platform. This can evidently be realized with the help of humanized information fusion (Amoretti et al. 2013) which is not a surrogate model of cloud computing architecture, rather a real-time IoT based data integration scenario that is capable of sensing and coalescing music of different genres (Zaslavsky et al. 2013); encouraged by the predictable mobile edge computing paradigm in the IoT domain.

1.2 Contributions

Key contributions of this proposed work are discussed as follows:

1.2.1 Qualitative humanized music fusion schema

A comprehensive explanation on three-layer music fusion architecture is provided where the source music data is sensed through the multiple sound sensors, accumulated in the storage and computed inevitably by the user involvement with a categorical understanding of the users.

1.2.2 Music as big data

In the context of music big data modernization, this is currently promising for music composers for influencing music metric efficiency using numerous analysing tools, and progress information relying upon algorithms which facilitate composers to compose attractive and catchy music melodies. We propose a rating matrix based on Big Data 'V' concept where a sensed and composed music in the system will be rated by music listeners.

1.2.3 The Edge-Cloud archetype for music computing

An edge computing archetype is presented in this contribution for music data and proposed system analysis. Sensed sound information by multiple sensors are stored in the edge devices primarily and then corresponding data and system entropy, system stability and efficiency of participated edge devices are analyzed. Music Cloud computing is a sound-oriented multimedia archetype which facilitates universal access to public groups of accessible resources. Data analyzing facilities in IoT analyzer such as Thingspeak can promptly facilitate with marginal managerial exertion over the edge of the Internet. IoT analyzing platform is accessed depending on processed musical data sharing for achieving soundness and reliable utility.

1.2.4 Analysis of latency and power dissipation

The proposed contribution also projects to calculate musical data transmission time, transmission and service latency.

1.2.5 Predictive analytics of information and system entropy

We illustrate the Information entropy in this contribution for defining an average amount of musical data in the system sensed by a set of sound sensors from a stochastic music information source for optimum resource allocation and storage. System entropy is also presented in this paper for measuring disorder level of the proposed closed but variable music fusion system. Our aim is to design an energy-efficient and stable IoT based music big data architecture.

1.2.6 Efficiency and stability analysis of IoT based music fusion

We develop a complete system that consists of physical sound sensing devices, edge computing devices, public cloud services and mobile applications for music composition which enable objects to connect and exchange data. The focus of developing such an environment is that each device can be distinctively recognizable over proposed inserted efficient computational arrangement however this is capable of stable inter-communication through obtainable Internet organization.

1.3 Paper Organisation

Rest of the paper has been organised as follows: Sect. 2 presents the works that were earlier discussed by the authors on big data, multi sensor data fusion and computing, IoT, edge computing and cloud computing. A state-of-the art comparative analysis among several approaches on music fusion in IoT environment has also been appended with the Sect. 2. The three-layer music information fusion architecture in ambient IoT paradigm has been analysed in Sect. 3. In Sect. 4, a detailed mathematical background of the proposed system has been presented. We have discussed proposed system analysis, performance metrics and evaluations in terms of the real-time case studies on latency, power dissipation, information entropy, system entropy, stability, efficiency and big data-based V-scheme in Sect. 5. Comparative analysis and discussion have been presented in Sect. 6 in the context of system entropy of the proposed systems in three different edge-cloud computational paradigms. Eventually, this paper has been terminated with the conclusions and future scopes in Sect. 7.

2 Related works

Analysis of music information fusion paradigm in IoT context is arguably sporadic, and up to this point of view, the researchers have taken numerous significant attempts in this context. Previous research contributions of the authors are characterized in diverse assessments for discussing the proposed paradigm. We have also illustrated several existing research approaches in Table 1 related to the proposed IoT based edge-cloud computing paradigm for humanized musical information fusion and system analytics.

2.1 Big data fusion

Researchers have analysed the evolution of data fusion-based systems (Ramírez-Gallego et al. 2018; García-Gil et al. 2018), sensing an absent object's occurrence in proximity is automatically conducted by smartphones, as the purpose runs in the background and collects the data (Roggen et al. 2013; Vakintis et al. 2016). By the great sensing bulk of smart handheld devices (Zaslavsky et al. 2013; Hao et al. 2017) and user-mobility, several services can be circulated relying on the structure of a reliable categorization. (Fan 2018). Big data has come to be a significant domain for versatile spaces of research areas like data fusion (Khalegi et al. 2013), machine learning, intelligent computing (Amoretti et al. 2013) and social networks (Babar and Arif 2018). The advancements of heterogeneous big data frameworks (Gandomi and Haider 2015) for billions of information processing based on the MapReduce paradigm defined in (Ramírez-Gallego et al. 2018) which has permitted for effective utilisation of data mining techniques and machine learning algorithms in diverse areas. Authors highlighted the requirement to advance proper and stable analytical approaches for leveraging enormous heterogeneous information volumes in semi-structured and unstructured multimedia objects such as video, audio, and text. Internet of Things (Sun et al.

Table 1 State-of-the-art comparison of several approaches for IoT analytics on humanized music information fusion

	Data Analytics	Multisensor data fusion	Information fusion: modelling and analysis	IoT analytics	Cloud computing-based approaches	Music Analysis
Information fusion (Ramirez-Gallego et al. 2018; Amoretti et al. 2013)	√	√	√	√	×	×
Multisensor data fusion (Khalegi et al. 2013; Zaslavsky et al. 2013; Rios 2014; Alamri et al. 2013; Durresi et al. 2018; Jia et al. 2017)	√	√	√	√	×	×
Internet of Things: system analysis (Vakintis et al. 2016; Sun et al. 2016; Hao et al. 2017; Park and Yen 2018; Jararweh et al. 2015; Lee et al. 2018)	√	×	√	√	√	×
Computational paradigm to support IoT analytics (Amoretti et al. 2013; Mashal et al. 2016; Darwish et al. 2017)	√	×	×	√	√	×
Big data analytics (Garcia-Gill et al. 2018; Roggen et al. 2013; Babar and Arif 2018; Gandomi and Haider 2015)	√	×	×	√	√	×
IoT analytics for Big data (Amoretti et al. 2013; Gandomi and Haider 2015; Cecchinel et al. 2014; Liu et al. 2015; Krishnan and Jayavel 2018; Sezer et al. 2018)	√	×	×	√	√	×
Cloud computing in IoT context (Hashem et al. 2015; Fazio et al. 2015)	√	×	×	√	√	×
Integration of IoT with Cloud (Liu et al. 2015; Bonomi et al. 2014; Arkian et al. 2017; Orsini et al. 2018)	√	×	×	√	×	×
Mobile edge computing paradigm (Dubey et al. 2015; Arkian et al. 2017; Venticinque and Amato 2018; Al-Osta et al. 2018)	√	×	×	√	×	×
Energy-aware profiling of mobile edge computing (Mukherjee et al. 2016; Elmore et al. 2014; Deng et al. 2017; Gray 2011)	√	×	×	√	√	×
Music analytics (Alvaro and Barros 2013; Tsai et al. 2017)	√	√	×	√	×	√
Musical pattern recognition and information retrieval (Roy et al. 2017, 2018)	√	×	√	×	×	√
Ambient IoT analytics on humanized music information fusion (Proposed contribution)	√	√	√	√	√	√

2016) associativity among physical and virtual world has been illustrated by the researchers for providing intelligent services using big data (Wu et al. 2014) based data mining. Current progression in sensor networks (Rios 2014) and communication paradigms (Hashem et al. 2015) has facilitated big data assortment. Big data analytics (Krishnan and Jayavel 2018; Sezer et al. 2018) have the projections in numerous inclusive fields comprising e-commerce, smart healthcare and industrial data management which deal with several thought-provoking issues on data warehousing, data mining and processing in big data contexts features for their billions of data variety, volume, velocity and versatility (Fan 2018).

2.2 Internet of Things

The latest research has instigated the impression of IoT (Hao et al. 2017) which accumulate information and smart devices through the internet and authorizes the device to device communication (Cecchinel et al. 2014; Park and Yen 2018). IoT framework is an exciting and significant platform for information storage, computations and data management (Orsini et al. 2018). Diverse platforms have been developing to mount applications in the smart room and smart city domains. (Lee et al. 2018). Cities also have huge concentrations of resources and facilities (Jararweh et al. 2015). A crowd-sourcing (Amoretti et al. 2013) application named Street bump that helps residents to improve their neighbourhood streets (Liu et al. 2015). The explosive development of Smart and IoT applications (Darwish et al. 2017) generates numerous technical challenges which necessitate inventive research efforts from both academic and industrial world, specifically for the growth of IoT environment in terms of efficiency, scalability, and reliability IoT environments (Mashal et al. 2016).

2.3 Edge and Fog computing

Authors have proposed a fog computing model, the current trend of a decentralized computational architecture, with a well-designed background schema. It also deploys applications and analysis scenario where information (Bonomi et al. 2014), computation and storage are distributed more efficiently and logically (Dubey et al. 2015) than conventional cloud computing environment (Mukherjee et al. 2016). The cloud computing paradigm has been incorporated with music composition applications (Roy et al. 2018) provided a dedicated music service layer for distributed music composition in cloud environment (Al-Osta et al. 2018). The fog and cloud computing schema and analysis are characterized in a distributed computing environment (Arkian et al. 2017).

2.4 Cloud computing

To facilitate applications of resource provisioning (Orsini et al. 2018) and substantial computing potential, IoT depends greatly on the cloud computing (Al-Osta et al. 2018). Cloud computing is the exercise of accessing remote servers for storing, managing and information processing rather than accessing the personal computing systems or local server. An additional novel proficiency is IoT that is increasing speedily in communication systems (Lee et al. 2018). Cloud infrastructure has not only a supplementary service provider and supports, but this is predictably constrained to individual benefactor data-centres that are being recognized (Elmore et al. 2014). Emerging developments in the field of cloud computing result in the diverse field of innovative music computing archetypes that can be obtained in next-generation cloud infrastructure (Alvaro and Barros 2013). These paradigms project on influenced domains like involving crowd and devices (Arkian et al. 2017), data-intensive figuring, virtualization, service-space, and machine learning.

3 Humanised music information fusion paradigm

3.1 Outline of the proposed architecture

In this subsection, we discuss a three-layered typical humanized music information fusion architecture in the context of the Internet of Things. In Fig. 1, the projected architecture has three diverse layers as physical layer, edge computing layer, and IoT Analyzing layer. These three layers are defined as follows:

3.1.1 Layer 1: physical layer

Bottommost layer of the proposed architecture contains sound sensors and mobile devices that sense unprocessed musical information from reliable sources of information. This layer also contains microcontrollers for physical computations over the sensor information.

3.1.2 Layer 2: edge computing layer

Elements of physical layer incorporate and communicate with the immediate next layer in the architecture, that is termed as the edge computing layer. The critical components of projected edge computing layer are managerial illustrations that contain edge computing tools, local storage, communication gateways etc. These components are task-specific in this proposed work like information processing, data accumulation, musical genre classification, local intelligent analytics, and transmission to the next layer.

3.1.3 Layer 3: IoT analysing layer

This layer embraces services to the end-users in the cloud. In the proposed paradigm, it provisions musical resource organization and information processing of music fusion activities to the IoT analyser (https://thingspeak.com). IoT analysing layer also contains system information (Venticinque and Amato 2018) warehouse that is capable of arranging and empowering service quality of edge computing paradigms. This layer stores processed musical information and set up a platform for music fusion incorporating different genres as the preferences of end-users and audiences. Furthermore, this layer comprehends the data analytics such as system latency and power dissipation (Elmore et al. 2014; Mukherjee et al. 2016), information and system entropy (Grey 2011), efficiency, and stability.

Figure 1 depicts a state-of-the-art humanised music information fusion paradigm in the context of Internet of Things. Described architecture has potentially two application-specific components. First one is device-driven component where pre-processed sensed data are propagated through microcontroller to the participated edge computing devices for information processing and computation. Next one is backend storage and services by the IoT analyser to analyse data for driving system analysis.

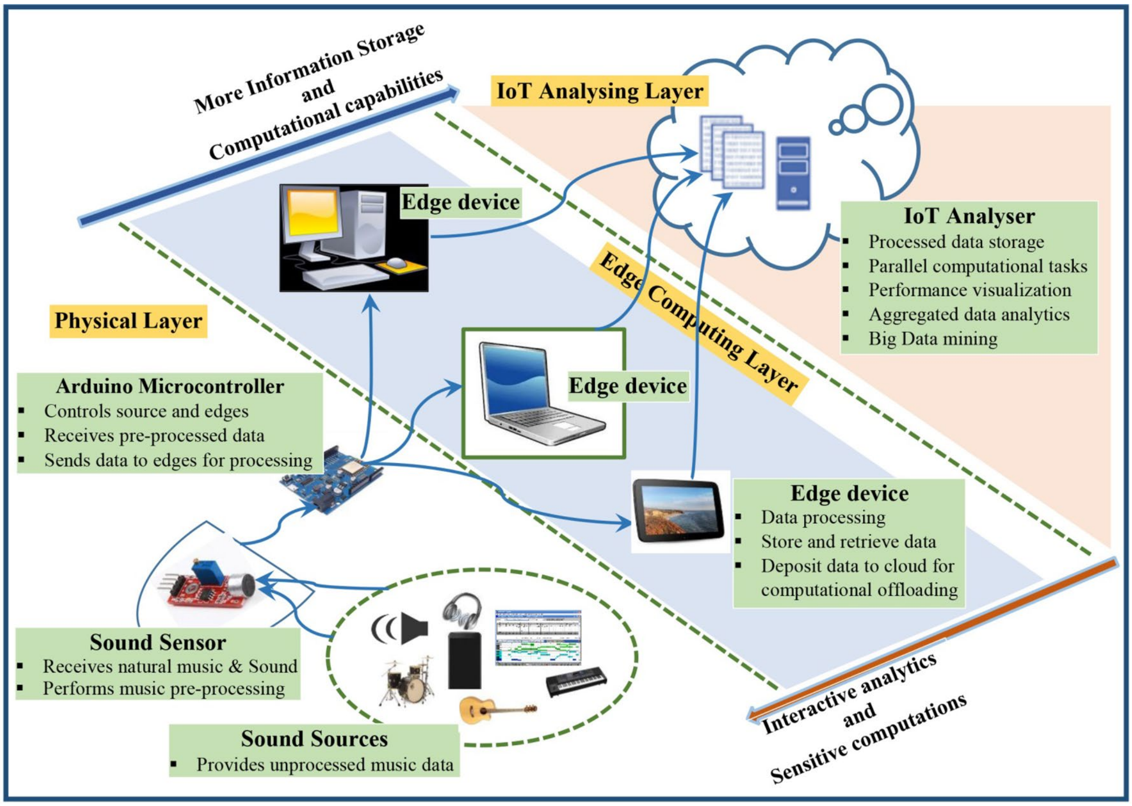

Fig. 1 Proposed humanized music information fusion architecture in IoT environment

4 System analysis: mathematical backgrounds of proposed music information fusion architecture

In this section, mathematical background of humanized music information fusion architecture in IoT environment has been presented by expressing composite entities and the operational functions involved with the proposed system. This section has been divided into two sub-sections; 4.1 presents the mathematical backgrounds of proposed architecture that is presented in Fig. 1 and Sect. 4.2 presents the 10-V schema of data analytics. During formulation of proposed mathematical background of music information fusion, total participated devices in all three dedicated tiers are assumed invariable over time.

4.1 Mathematical Backgrounds: Architecture analysis

Definition 1 (Physical sources): Physical sources can be classified into two distinct sets such as source data and multi-modal sensor devices. Physical sources, denoted by Ƥ, is defined as a set of five tuples.

$$\text{Ƥ} = \langle S_s, \ S_{Id}[i], \ T_d, t_s, \ \partial \rangle, \tag{1}$$

where, S_s is the sound source. $S_{Id}[i]$ is a 1-D array which specifies unique id of every sources. T_d defines source device type like sound devices, instrumental sound sources etc. t_s represents duration of sensing sound from sources. ∂ denotes the surroundings of sources.

Definition 2 (Music fusion attributes): Music fusion schema is symbolized as F_M and can be defined by a five-tuple set.

$$F_M = \left\langle T_f, P_f, G_m, I_f, C_f \right\rangle, \tag{2}$$

where, T_f represents the type of fusion such as vocal fusion (V_T) or instrumental fusion (I_T). Hence, T_f can be represented as $T_f = \langle V_T, \ \mathrm{I}_T \rangle$, where, $V_T = \{v_1, \ v_2, \ldots \ldots .., \ v_v\}$ and $I_T = \left\{i_1, \ i_2, \ldots \ldots ., i_i\right\}$. P_f is the type of fused composition performance. G_m denotes the music genre such as Jazz, rock, funk, classical, pop and so on. I_f represents the type of instruments used in a specific music fusion. C_f denotes the precise user criteria for composing of fusion music.

Definition 3 **(Multi-modal sound sensors)**: Participated sensors S_{part}, can be defined as a set of five-tuple.

$$S_{part} = \langle P_{Id},\ \rho,\ \ell,\ \Gamma_s, \mathcal{S}\rangle, \tag{3}$$

P_{Id} is the unique id of physical sound sensor. ρ is the sensor pattern like dynamic moving coil microphone sound transducer, Condenser Microphone, Electrets Condenser Microphone etc. ℓ denotes the optimum geo-spatial location and direction of physical sensor. Rest of the tuples are defined as follows. $\mathcal{S}$ measures the size or cross-sectional area of the sound sensor microphone. More area $\mathcal{S}$ denotes more data absorbing capability by the sensor device.

Definition 4 **(Features of sound sensing devices)**: The features of the participated sound sensing devices are symbolized by Γ_s, and it can be defined by a seven-tuple set in Eq. (4.)

$$\Gamma_s = \langle \mathrm{R}, \Omega, \xi, i_m, \mathrm{g}, \Phi, \varphi_a\rangle, \tag{4}$$

where, R denotes maximum voltage of the sensor. Ω is sensitivity of the device microphone. ξ represents the current. i_m is the device impedance. g denotes the voltage gain during sensing. Φ is the corresponding pitch value of the data and φ_a signifies the unwanted acoustic noise during unprocessed information sensing.

Property 1 The operational mapping from the music sources S_S upto the set of participated sound sensors S_{part}, symbolised as $f' : \tilde{S}_S \to \tilde{S}_{part}$ is injective.

Proof The mapping $f' : \tilde{S}_{S_1} \to \tilde{S}_{part_1} \big| (S_{S_1} \in S_S, S_{part_1} \in S_{part})$ defined by, $f(S_S) = S_{S_1} + \{S_S\}$ where, $\{S_S\} \neq S_{S_1}$ and $\{S_S\} = \{S_{S_2}, S_{S_3}, \ldots, S_{S_m}\}$ is one to one as $f(S_{S_1}) = v(S_{part_1})$ $\Rightarrow S_{S_1} + \{S_S\} = S_{part_1} + \{S_{part}\} \Rightarrow S_{S_i} = S_{part_i} \forall S_{S_1} \in S_S$, $S_{part_1} \in S_{part}$.

4.1.1 Illustration

The mapping from sound sources to the participatory sound sensors, which is represented in Fig. 2 signifies that one active sensor can sense single data packet at a time from a sound source in physical layer of proposed architecture.

Definition 5 **(Edge devices)**: Edge devices denoted as E, defined by eight-tuple.

$$\mathrm{E} = \left\langle Id_e, T_e, S_e, S_c, \mathbf{G}_c, S_e, \mathrm{T}_{sensorToEdge}, L_{sensorToEdge} \right\rangle, \tag{5}$$

where, Id_e indicates unique ID of the edge devices.T_e denotes the type of edge device. Mathematically, set of components is provided where $T_e = \{T_{e_1}, T_{e_2}, \ldots, T_{e_n}\}$ symbolizes event-set that all edge devices monitor the system states. S_e denotes the mode of edge device whether the device is ON or OFF mode. S_e signifies the ACTIVE or IDLE state of the edge device. $\mathrm{T}_{sensorToEdge}$ presents the data transmission time and $L_{sensorToEdge}$ is the system latency when data transmits from music sources to edge devices through sensors.

Property 2 Mapping from the participatory sound sensors P upto the edge devices E, designated by $f' : \tilde{\mathrm{P}} \to \tilde{\mathrm{E}}$, holds bijective relation.

Proof The functional mapping, $f' : \tilde{\mathrm{P}} \to \tilde{\mathrm{E}}$can be denoted as $f(\mathrm{P}) = \mathrm{P}_1 + \{\mathrm{P}\} \big| \{\mathrm{P}\} \neq \mathrm{P}_1$ and $\{\mathrm{P}\} = \{\mathrm{P}_2, \mathrm{P}_3, \ldots, \mathrm{P}_p\}$ and $f(E) = E_1 + \{E\} \big| \{E\} \neq E_1$ and $\{E\} = \{E_2, E_3, \ldots, E_e\}$, then functional mapping f is surjective which can be written as $f(P) = E$.

The mapping $f' : \tilde{\mathrm{P}}_1 \to \tilde{E}_1 \big| (\tilde{\mathrm{P}}_1 \in \mathrm{P}, \tilde{E}_1 \in E)$ denoted by $f(\mathrm{P}) = \mathrm{P}_1 + \{\mathrm{P}\}$ where, $\{\mathrm{P}\} \neq \mathrm{P}_1$ and $\{\mathrm{P}\} = \{\mathrm{P}_2, \mathrm{P}_3, \ldots, \mathrm{P}_p\}$ is one to one mapping as $f(\mathrm{P}_1) = v(E_1) \Rightarrow \mathrm{P}_1 + \{\mathrm{P}\} = E_1 + \{E\}$ $\Rightarrow \mathrm{P}_j = E_j \forall \mathrm{P}_1 \in P, E_1 \in E$.

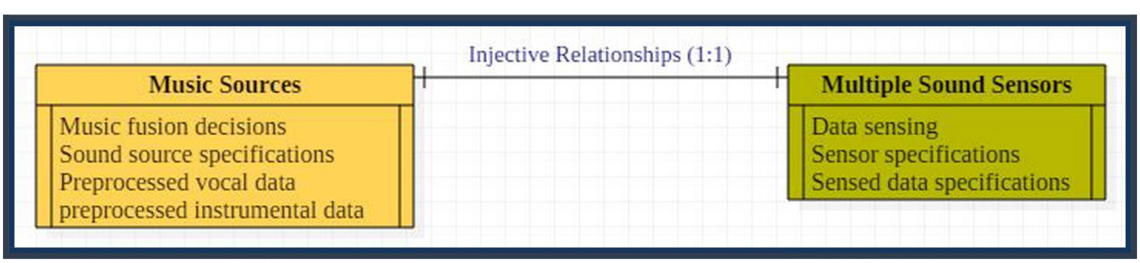

Fig. 2 Relationship between music sources with sensing devices

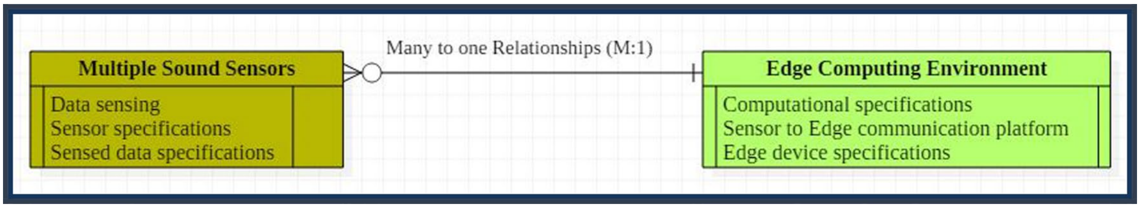

Fig. 3 Relationship between set of multiple sound sensors and edge computing devices

4.1.2 Illustration

The mapping from participatory sound sensors to the edge computing devices, shown in Fig. 3, illustrates that all participatory sensors can transmit pre-processed data from the sound source to an edge computing device for system computations and storage.

Definition 6 (Specifications of IoT analyser): IoT analysing environment is defined by **I** and is a set of five-tuple. We have analysed the proposed system by Thingspeak IoT analysing tool (https://thingspeak.com).

$$\mathbf{I} = \left\langle Id_{instance}, \mathrm{T}_{edgeToCloud}, L_{edgeToCloud}, S_{IoT}, \mathbf{P} \right\rangle \tag{6}$$

where, $Id_{instance}$ is the instance identification number of the IoT analyser. $\mathrm{T}_{edgeToCloud}$ and $L_{edgeToCloud}$ denote the information processing time and system latency respectively of the transmitted data from the edge computing devices to the IoT analyser. S_{IoT} denotes the data storage available in the system. Relevant power dissipation in the proposed system is symbolized by **P**.

Property 3 The functional mapping from the participated edge computing devices$E$ to IoT analysing layer **I**, can be written as $f'(.) : \tilde{\mathrm{E}} \rightarrow \tilde{\mathbf{I}}$ holds Many-to-One relationship.

4.1.3 Illustration

The mapping, in Fig. 4, from functional edge computing devices to IoT analysing layer illustrate that participated edge devices E can offload the processed data to a single public IoT analyser through the authenticated channel for storage and services in the projected information fusion scenario.

4.2 Mathematical backgrounds: data analytics

The concept of big data drives beyond of conventional 3-V schema with unaided volume, variety and velocity (Zaslavsky et al. 2013). We have illustrated 10-V schema in this contribution with their background specifications.

Definition 7 (Value): The Value is denoted as V_1, and it can be defined by eight distinct tuples.

$$V_1 = \left\langle A, \rho, \varpi, E, P, H_{inf}, Eff, \Theta \right\rangle \tag{7}$$

where, A and ρ are the amplitude and frequency respectively. ϖ is the data characteristics. E and P denote the energy and power consumption for storing a data value in the system. H_{inf} is the information entropy of source data value. Eff is the parameter for measuring the data efficiency in proposed system. Θ defines the data optimization.

Definition 8 (Volume): The Volume is denoted as V_2, and it can be defined by four distinct tuples. V_2 is defined as follows:

$$V_2 = \langle \mathrm{T}, Id_v, \Delta, \mathbb{Q} \rangle \tag{8}$$

where, T is the type of the data volume. Individual data volume has the unique id, denoted by Id_v. Δ denotes the capacity and $\mathbb{Q}$ defines the category or specification of the volume.

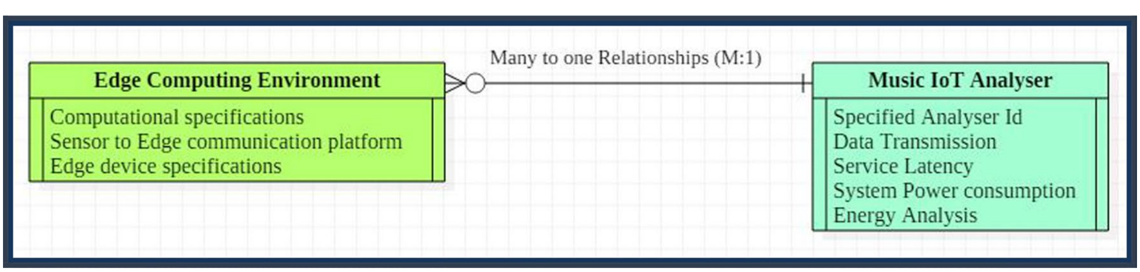

Fig. 4 Relationship between edge devices and music IoT analyser

Definition 9 (Velocity): Velocity denotes speed at which the information is being created or restored. The velocity is denoted as V_3, and it can be defined by a set of three tuples. V_3 is defined as follows:

$$V_3 = \left\langle \mathfrak{R}_{V_2}, \Delta, \mathrm{T_p} \right\rangle \tag{9}$$

where, $\mathfrak{R}_{V_2}$ denotes the rate of the volume V_2. D denotes the sensing capacity of the sensor. T_p is the processing speed and it can be defined as follows:

$$\mathrm{T_p} = \langle \Delta_{data}, t \rangle \tag{10}$$

where, Δ_{data} denotes the data volume and t is the information processing time.

Definition 10 (Variety): The variety is denoted as V_4, and it can be defined by a set of four-tuple. V_4 is defined in Eq. (11.) When variety is analysed in the context of big data, we have to analyse not only structured information but unstructured and semi-structured information as well. Most sensed data are seemed to be unstructured, but besides multimedia data there are also log documentations, click information, machine and sensor-gathered data and so on.

$$V_4 = \langle \mathrm{R}, \mathbf{\Gamma}, Id_d, \mathrm{Z}_{cl} \rangle \tag{11}$$

$$P = \langle \alpha, \beta, \gamma \rangle \tag{12}$$

where, $\mathbf{\Gamma}$ defines the data type. Id_d is the unique identification index of data variety in the proposed system. Z_{cl} is defined as the information cluster or the group of homogeneous data types. P defines the numerous data features and it can be defined by a set of three tuple. α, β and γ are the variety of data such as structured, semi-structured and unstructured respectively.

Definition 11 (Viscosity): Viscosity is denoted as V_5, and it can be defined by a set of three tuples. V_5 is defined as follows:

$$V_5 = \left\langle \mathrm{R}_{V_2}, \theta, \xi \right\rangle \tag{13}$$

$$\mathrm{R}_{V_2} = \langle \Upsilon_d, \dagger, \pi, \Omega \rangle \tag{14}$$

R_{V_2} is the resistance to flow in the data volume V_2. The resistance can be defined by a set of four-tuple. Υ_d represents different data sources, † is the data friction of integration through the system, π is information flow rate and Ω is defined as processing required to turn the data into insight. θ denotes the agile integration of the system and ξ illustrates the event processing through the channel.

$$V_6 = \langle \mathbf{\Gamma}, \mathrm{C} \rangle \tag{15}$$

where, $\mathbf{\Gamma}$ defines the data type and C denotes as pathways of communication. The data type $\mathbf{\Gamma}$ can be illustrated by a set of five-tuple, which is defined in Eq. (16).

$$\mathbf{\Gamma} = \langle U, \Lambda, \ell, \lambda, \mathrm{M} \rangle \tag{16}$$

$$U = \langle \mathcal{R}, \mathcal{D}, \mathcal{M} \rangle \tag{17}$$

where, U denotes uncertainty because of information inconsistency and incompleteness; It can also be described by three attributes in Eq. (17). R, D and M denote as process, information and proposed system model. Λ illustrates system ambiguities, ℓ denotes the data processing latency, λ is the data deception and M signifies the proposed schema approximation.

Definition 12 (Visualisation): Visualisation is denoted as V_7, and it can be defined by a set of three tuples. V_7 is defined as follows:

$$V_7 = \langle Id_A, \Gamma_A, \mathrm{A} \rangle \tag{18}$$

where, Id_A denotes the unique application Id; Γ_A is the application type and A is the relevant data analytics environment.

Definition 13 (Validity): Validity is denoted as V_8, and it can be defined by a set of four tuples. V_8 is defined as follows:

$$V_8 = \langle \mathcal{A}, \mathrm{S}, \mathbb{Q}, \aleph \rangle \tag{19}$$

where, $\mathcal{A}$ is defined as data accuracy; S defines services; $\mathbb{Q}$ denotes data quality and $\aleph$ measures the decision making.

Definition 14 (Volatility): Volatility is denoted as V_9, and it can be defined by a set of five tuples. V_9 is defined as follows:

$$V_9 = \langle C, \mathrm{I}, \mathbf{R}, A, \mathcal{R} \rangle \tag{20}$$

where, C illustrates data consideration; I denotes Issues; $\mathbf{R}$ represents rules; A displays availability and $\mathcal{R}$ defines data rating in the context of social recommendation.

Definition 15 (Virality): Virality designates how hurriedly data gets distributed across data fusion and crowdsensing networks. Virality is denoted as V_{10}, and it can be defined by a set of five tuples. V_{10} is defined as follows:

$$V_{10} = \langle \Upsilon_i, \mathbb{C}_i, \mathrm{H}_i, H_s, \mathrm{Z} \rangle \tag{21}$$

where, Υ_i denotes information type; $\mathbb{C}_i$ defines data characteristics; H_i denotes information entropy; H_s describes system entropy, Z defines uncertainty of the proposed system.

5 Performance metrics and evaluations

In this section, performance metrics and analytics for IoT-based humanized music information fusion paradigm are discussed. Figure 5 presents the flow of activities in the proposed humanized music information fusion schema in the context of Internet of Things. This section is classified into eight subsections. System latency is analyzed in sub-Sect. 5.1. Sub-Sect. 5.2 presents the analysis of power consumption of the proposed system. Information and system entropy are illustrated in the subsections 5.3 and 5.4 respectively. System stability and efficiency are predicted and analyzed in subsections 5.5 and 5.6. Eventually, this Sect. 5 is terminated with a case-study and its demonstration on proposed big data V-schema for resource allocation strategy in sub-Sect. 5.7.

5.1 Service and transmission latency

The term service latency is primarily the system response time where a computing device is responsible to receive a data packet request, sent by the IoT analyzing device within a specific application environment. This is measured by sum of information processing latency and data transmission latency (Roy et al. 2018) within an IoT system. In the proposed system, we have assumed that the network communication delay is few even negligible owing to higher level bandwidth channel in Thingspeak IoT analyzer (http://www.mathworks.com/help/thingspeak).

Let us assume that, the data transmission latency for transmitting N number of data packets from the source sensor devices to the edge devices is $L_{sourceToEdge}$, that can be defined as:

$$L^{N}_{sourceToEdge} = \sum_{i=1}^{N} (L^{i}_{S} + L^{i}_{P}) \tag{22}$$

where L_S and L_P denote service and data transmission latency respectively for transmission of sensor data from sensor to edge devices.

Data preprocessing latency depends on component-specifications in the physical layer of the proposed system. We can adopt that, L_{sensor} and $L_{Arduino}$ are data pre-processing latency of participated sensors and microcontrollers for individual data packet. For measuring data pre-processing latency L^{Total}_{P} within physical layer over N data packets, can be calculated using Eq. (23).

$$\text{Data pre} - \text{processing latency},\ L^{Total}_{P} = \sum\nolimits_{i=1}^{N} (L_{sensor} + L_{Arduino}) \tag{23}$$

After pre-processing of N data packets, transportation latency from sensors to IoT analyzing layer is measured which is expressed by the summation of data transportation time from physical layer to edge computing layer and edge to IoT analyzing layer. These are denoted as $L_{sourceToEdge}$ and

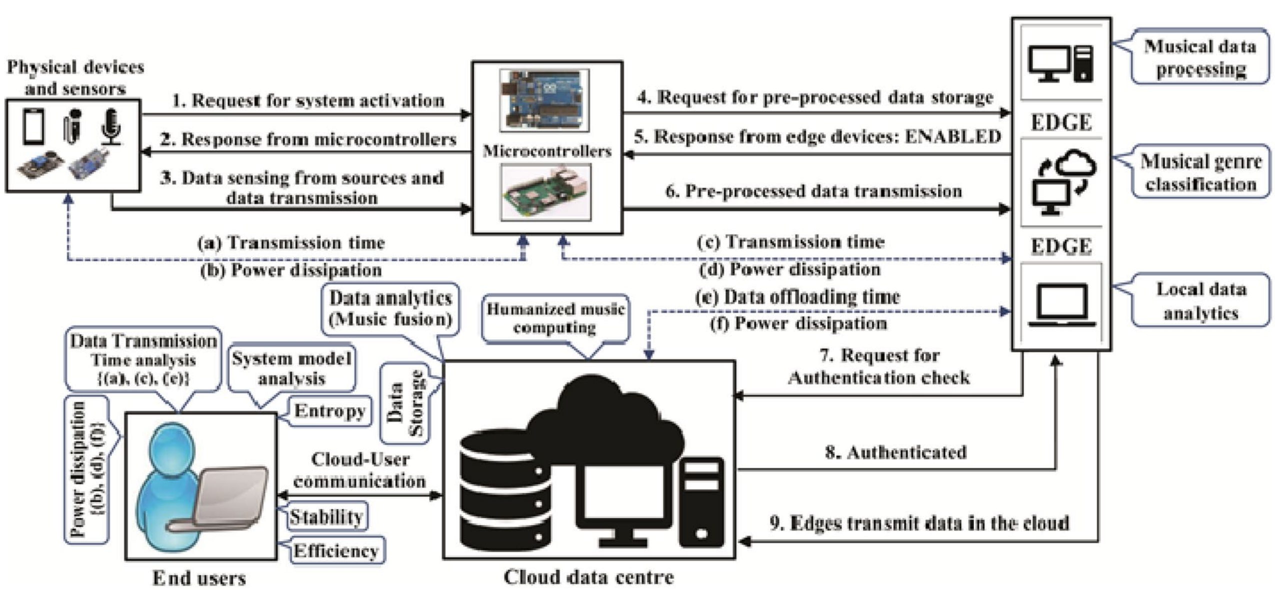

Fig. 5 Flow of activities in the proposed humanized music information fusion schema in the context of Internet of Things

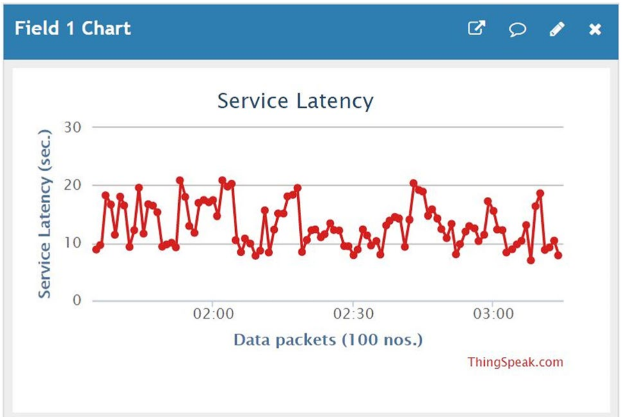

Fig. 6 Service latency of the proposed system in edge device against number of music data packets

$L_{edgeToIoT}$. Data transportation latency for N data packets is assumed as L_{pd} and can be measured by Eq. (24).

$$\text{Data transportation latency, } L_{pd} = L^{N}_{sourceToEdge} + L^{N}_{edgeToIoT} \tag{24}$$

Service latency is the incorporation of all intermediate latencies within the proposed system when physical devices receive requests from the IoT analyzer and respond accordingly to the next-layer elements. Intermediate network delays may be arisen for flexible bandwidths of the channels during data transmission. Hence, considering intermediate system delays, we can evaluate the service latency $\Lambda_{service}$ for can be measured Ndata packets by Eq. (25). The service latency graph of our proposed system is presented in Fig. 6.

$$\text{Service latency, } \Lambda_{service} = L^{N}_{Total} = L^{N}_{sourceToEdge} + \sum_{i=1}^{N} L^{IoT}_{edge} + L^{total}_{delay} \tag{25}$$

The information transmission latency, symbolized as Λ_{Trans}, in presented in Eq. (26).

$$\text{Transmission latency, } \Lambda_{Trans} = L^{N}_{total}(or, \Lambda_{service}) - (L^{total}_{delay} + L_{p}{}^{total}) \tag{26}$$

where, L^{N}_{total} $or, \Lambda_{service}$ is the service latency of the proposed system that is mentioned in Eq. (25); L^{total}_{delay} denotes the system and network delay and finally $L_{p}{}^{total}$ denotes previously-defined data pre-processing latency in Eq. (23). In Fig. 6, the graphical representation of service latency is shown for 100 nos. individual sensed data packets in our proposed IoT-based experimental and computational environment.

5.2 Power dissipation

In this section, we discuss power dissipation strategy for music fusion architecture in IoT environment, where musical data are sensed by sound sensors in physical layer, then pre-processed data are sent to the edge devices for computations. Eventually, the processed data are transmitted to IoT analysing layer from edge computing tier for evaluating IoT system performance. User can access the information by the device-centric applications. Principal approach behind the utility of project schema is to dissipate low power by the system (Roy et al. 2018) in smart IoT devices. Figure 7 represents the power dissipation of the proposed system against individual music data packets using Thingspeak IoT analyser.

We assume that the power is consumed when the data packets are transmitted from edge devices to IoT analysing layer, is denoted by $W^{Edge\rightarrow IoT}_{Trans}$ and it is evaluated by Eq. (27). All the parameters used for evaluating power dissipation are illustrated in Table 2.

$$W^{Edge\rightarrow IoT}_{Trans} = (W_{edge\_trans} \times R_{amt\_exp})/R_{exp} \tag{27}$$

then, we assume that the power is dissipated when the data packets are received in the channel of IoT analysing tier which are transmitted from edge devices, is denoted by $W^{Edge\rightarrow IoT}_{Rcv}$ and it is evaluated by Eq. (28).

$$W^{Edge\rightarrow IoT}_{Rcv} = (W_{edge\_rcv} \times R_{amt\_imp})/R_{imp} \tag{28}$$

Power dissipation during data packet export to the IoT analyzing devices from intermediate edge devices, is denoted by $W^{Edge\rightarrow IoT}_{Export}$ and it is measured by Eq. (29).

$$W^{Edge\rightarrow IoT}_{Export} = W_{edge\_import} \times [(L_{R\_edge\rightarrow IoT}/P_{edge}) + (N_{D_1}/I_{IoT})] \tag{29}$$

Total power dissipation for the proposed system will be the sum of step-wise defined power consumption in Eqs. (27), (28) and (29) and are denoted by $W^{Edge\rightarrow IoT}_{Trans}$, $W^{Edge\rightarrow IoT}_{Rcv}$ and $W^{Edge\rightarrow IoT}_{Export}$ and it is evaluated by Eq. (30.1) and (30.2).

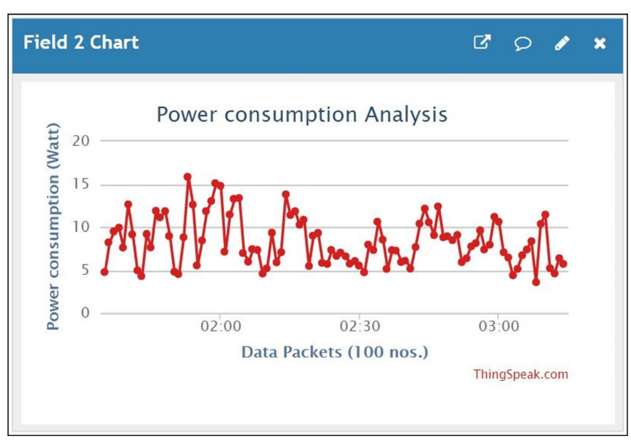

Fig. 7 Power consumption analysis of the proposed system against number of music data packets

Table 2 Parameters used in Power calculation of the proposed system

Parameter	Definition	Parameter	Definition
W_{edge_import}	Power consumption rate of edge device during data export	R_{exp}	Data transmission rate for export
W_{edge_trans}	Power consumption rate of edge device during data transmission	R_{imp}	Data transmission rate for import
W_{edge_rcv}	Power consumption rate of edge device during data import in IoT analyzing tier	$R_{ant-exp}$	Data amount transmitted during data export
W_{edge}	Speed of computable edge device	R_{amt_imp}	Data amount transmitted during data receive
P_{edge}	Propagation velocity of edge device	N_{D1}	Set of data instructions to be executed for the code to be exported
$I_{\_IoT}$	Data propagation speed of IoT analyzer	T_{D1}	Sensor utilization time
$L_{edge\to IoT}$	Length from edge device to executable IoT device	W_{D1}	Power consumption rate of microcontroller (Arduino D1) of sensor access to edge device
$L_{R_edge\to IoT}$	Length from requesting edge device to IoT analyzing tier		

$$W_{Total}^{Sensor\to IoT} = \left[W_{Trans}^{Edge\to IoT} + W_{Rcv}^{Edge\to IoT} + W_{Export}^{Edge\to IoT} \right] + [T_{D_1} \times W_{D_1}] \tag{30.1}$$

$$\begin{aligned} W_{Total}^{Sensor\to IoT} = & [\{(W_{edge\_trans} \times R_{amt\_exp})/R_{exp}\} \\ & + \{(W_{edge\_rcv} \times R_{amt\_imp})/R_{imp}\} \\ & + W_{edge\_import} \times \{(L_{R\_edge\to IoT}/P_{edge}) \\ & + (N_{D_1}/I_{IoT})\}] + (T_{D_1} \times W_{D_1}) \end{aligned} \tag{30.2}$$

5.3 Information entropy

Information entropy refers the amount of information or data that is sensed from a stochastic data source within a specific system environment. More information in a system signifies more uncertainty or randomness of proposed event. Preliminary schema of an IoT based data fusion system is comprised of three essential ingredients, the data source, communication gateway and storage. In our proposed schema, the three ingredients are sound sensors, microcontroller, such as Arduino D1 and edge devices respectively. Entropy offers optimum limitations on length using probable shortest path for sensing data from sound sources with minimal lossless compression; channel capacity of sound sensing device will be lesser than the capacity of communication gateway like Arduino D1 and edge devices should be provided a reliably computable and storing capacity.

We are to discuss that how much information is responsible to carry the minimum entropy of the proposed system to be stable or efficient. We assume that our proposed IoT system for music data fusion schema has the maximum information capacity of the storage device N bits and N_i denotes total number of sensed data packets by the sensor devices. Then, the information entropy denoted by H_{inf} is

$$H_{inf} = \sum_i \sum_{P_i} \text{K}.\ ln({}^{N-P_j}\text{C}_{P_i}) \tag{31}$$

where, Kis the positive constant, N denotes system capacity of the storage device (in bits) and N_i denotes total number of sensed data packets. P_i denotes the number of bits of the newly sensed data by the sensing devices and P_j is assumed as existing or pre-allocated number of bits in the proposed system. So, as per system stability and modelling an efficient system concerns, we assume that system has the optimum information for minimum randomness when the condition will be satisfied that is expressed in Eq. (32).

$$P_j = P_0 + P_i \tag{32}$$

Proof For system stability, we can say that

$$\frac{dH_{inf}}{dP_i} = 0 \tag{33}$$

It implies that,

$$\frac{d}{dPi}\left[K.ln(\frac{(N-P_j)!}{(N-P_j-P_i)!P_i!}) \right] = 0 \tag{34.1}$$

Hence,

$$N = P_j + P_i \tag{34.2}$$

We show the analysis of sensed information entropy in Fig. 8 with respect to the available number of musical data packets which are sensed by the multiple sound sensors and stored in edge device. We illustrate that for a certain criterion which is expressed in Eq. (34.2), the optimum information entropy will be achieved that is described in Algorithm 1. Hence, we obtain the peaks when total data size of specific incoming data packets will be equal to the data size of the left-over data packets of system storage.

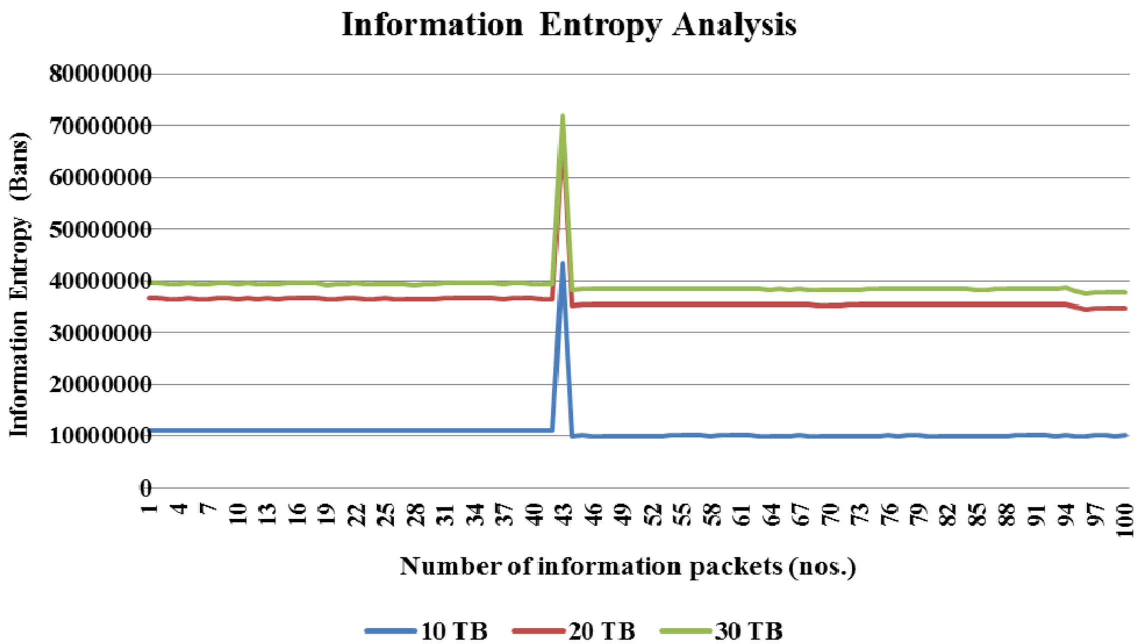

Fig. 8 Representation of Information entropy of proposed data fusion architecture against data packets in the system

Algorithm 1: Information Entropy analysis

Initialisation of inputs: No. of Data packets (W), Individual size (P_i), Existing allocated bits (Q_W), Total storage size (N)

Output: Information Entropy, H_{inf}

Initialize: Obtain W and P_i in S_0

Case 1: N invariant

If (N has a specific value)

Then Iteration continued

Else computational error (Logical Error)

Break;

End If

Case 2: While N variant

For $j = 1$ to count$\left[N_{\max}\right]$

Compute $N = N \times j$;

End While

Iteration: For $W = 1$ to $|U|$ //In proposed system $U = 100$

$P_W = S_0\left(P_W\right)$

$H_{inf} = \left(N - Q_w\right) \times log\left(N - Q_w\right) - \left(N - Q_W - P_i\right) \times log\left(N - Q_W - P_i\right) - P_i \times log\left(P_i\right)$

$Q_W = Q_W + P_W$

End For

STOP

5.4 System entropy

System entropy can also arguably be defined as the thermodynamic entropy (Grey 2011). The system entropy is the measure of randomness of a closed, isolated and changeable system. It can be defined by three essential system components such as system power consumption, service latency

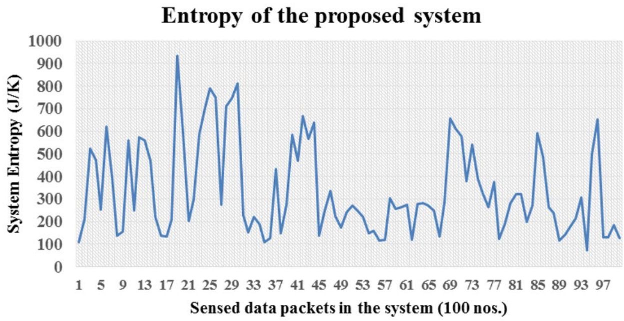

Fig. 9 System entropy analysis with respect to sensed data packets

and system temperature. System entropy is denoted as H_{sys} and can be expressed as in Eq. (35),

$$\text{System Entropy, } H_{sys} = W_{Total}^{Sensor \to IoT} \times \Lambda_{service} \times log_{10}(T_2 - T_1) \tag{35}$$

where, $W_{Total}^{Sensor \to IoT}$ denotes the total power dissipation of the proposed system expressed in Eq. (34.2). $\Lambda_{service}$ is the service latency that is defined in Eq. (25). T_1 denotes temperature of source sensor device and T_2 signifies the system temperature that is the computational edge device. Figure 9 shows the entropy of our proposed system when this system senses the data packets from natural and physical sound sources.

5.5 System stability

System stability refers as the capability of system to persist invariant over time under specified or realistically predictable circumstances of usability and storage. For IoT system stability, we can assume the condition in Eq. (36) should be satisfied.

$$\text{System stability condition, } \frac{dH_{inf}}{dP_i} = 0 \tag{36}$$

where, H_{inf} denotes information entropy and P_i is the number of newly sensed data received by the sensing devices.

$$\text{It implies that, } \frac{d}{dP_i}\left[K.ln\frac{(N - P_j)!}{(N - P_j - P_i)!P_i!}\right] = 0 \tag{37}$$

where, Kis the positive constant, N denotes system capacity of the storage device (in bits) and P_j is assumed as existing or pre-allocated number of bits in the proposed system.

$$\text{Hence, } N = P_j + P_i \tag{38}$$

So, as per system stability concern, we can say that the proposed system will be stable when the condition in Eq. (38) will be satisfied.

5.6 System efficiency

Efficiency refers to the effectiveness for avoiding degenerative substances, vitality, determinations and time for doing approximately productive outcomes. This is the degree of extent upon that inputs are well utilized for a projected assignment or outcomes. It is a measurable perception and mathematically determined by the ratio of desired output to total input. In our proposed IoT environment for music fusion schema, the condition of efficiency can be expressed as

$$\text{System efficiency, } \eta = \left[\frac{H_i}{H_{\max}}\right] \tag{39}$$

where, η denotes system efficiency, H_i is the information entropy while allocating i^{th} data packet and $H_{\max}$ denotes the state when system reaches maximum entropy. In Fig. 10, we show the normalized rate of efficiency over the data storage size in the participated storage devices. Figure 10 also illustrates that with 750 GB of system storage size provides optimum system efficiency for sensing and computing of the processed data packets in the proposed system.

Correlations among system elements can be expressed as some conditions in terms of information and system entropy, efficiency and stability analysis over proposed architecture of the system.

- More number of random information in a system denotes more uncertainty of a system and can be stated as, therefore, system is more stable.
- A system will be less efficient when more system uncertainty (system entropy) occurs.
- More data synchronization among system information indicates less uncertainty and system has less entropy as well.

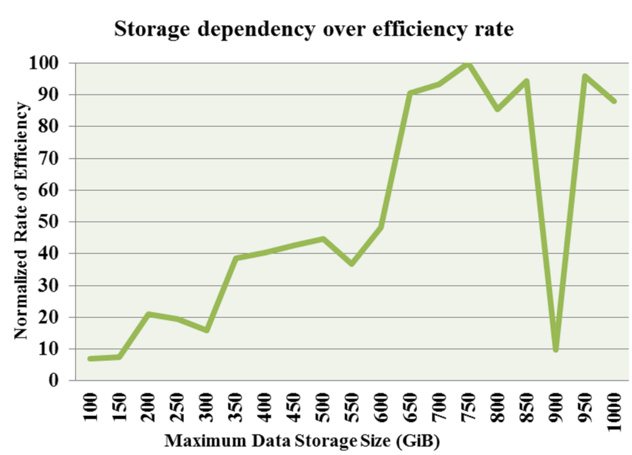

Fig. 10 Representation of the effieciency rate with respect to the data storage capacity in the system

Algorithm 2: Efficiency and Stability analysis
Data packet size: n bit
Storage capacity: N bit $N >> n$
Occupied storage: N_0 bit
Empty Space: $(N - N_0)$ bit
No. of microstate: ${}^{(N-N_0)}C_n$
So, H will be maximum, i.e. H_{max} when $(N - N_0) = 2n$
So, If $(N - N_0 - 2n) \approx 0$ System has it's maximum H for which the efficiency or stability is maximum
As, $\eta = \dfrac{H}{H_{max}}$ which will tend to its max value as $H \rightarrow H_{max}$

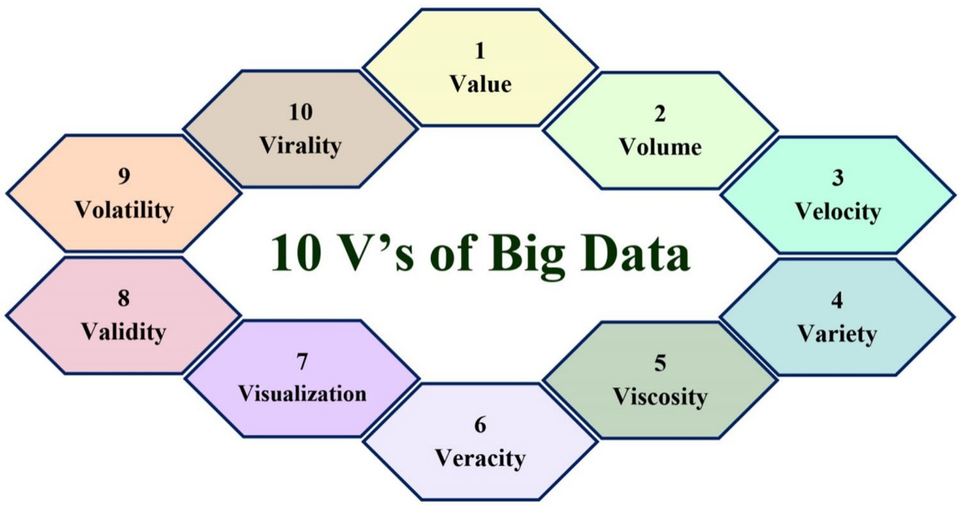

Fig. 11 Representation of Big data '10-V'

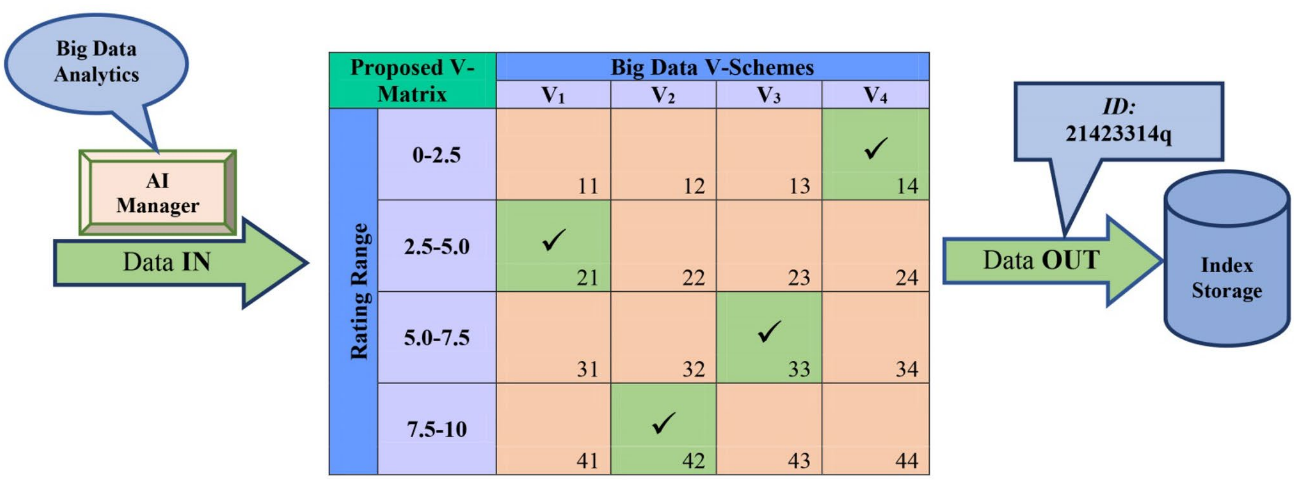

Fig. 12 Demonstration of Big data V-scheme for visualising resource allocation strategy and users' music rating

5.7 Proposed Big Data V-Scheme for resource allocation

In our proposed and novel V-scheme, we have used the big data analytics scheme for allocating sensed data in system resources that is in the IoT instance from multiple sound sensors using intelligent allocation strategy. For simplicity of the system, we have used only four 'V' of big data, i.e., value (V_1), volume (V_2), velocity (V_3) and variety (V_4) in our system in order to explain how it works. Although in real-time system scenario, we can extrapolate proposed '10-V' schema in this paper in Fig. 11 for making a more stable rather complex system.

Initially we have to classify the data in terms of different rating of 'V' and giving them a distinct identification number. AI manager gives the rating for a different data by using the big data analytics. For an example, let us assume that a data 'X' has a rating of 2.5 for V_1, 7 for V_2, 4.5 for V_3, 1 for V_4. We have the matrix form that is demonstrated in Fig. 12.

Information entropy relates how much information one system can achieve with much more arrangement or synchronization. In our proposed schema we use 4×4 matrix form. Now in general for $m \times n$ form we have the expression for system entropy is,

$$H = \sum_{P_0=1}^{mx} \frac{n.log(mx - P_0)}{(mx - P_0)^n} \tag{40}$$

where, P_0 denotes the number of data packets in the system while a new packet arrived in system; m is row value; n is column attributes and x defines the number of microstate under every small matrix cell, that is termed as the Dynamic Index Allocator. Hence, Total number of data packets which can be allocated to this system is $(mx)^n$. Hence, eventually we can state that by increasing the value of m, x and n we can increase our storage capacity of the system.

5.7.1 Advantages of the proposed V-scheme strategy

There are several advantages of the above proposed strategy in Big Data V-schema in the context of resource allocation,

i. In our modern civilization especially in this Big Data era we are losing the synchronization of putting the proper data to specific place without losing its identity and also keeping its features safe so that we can recall it when we need it. Now by varying the different type of 'V' we can ensure that each and every data is safe

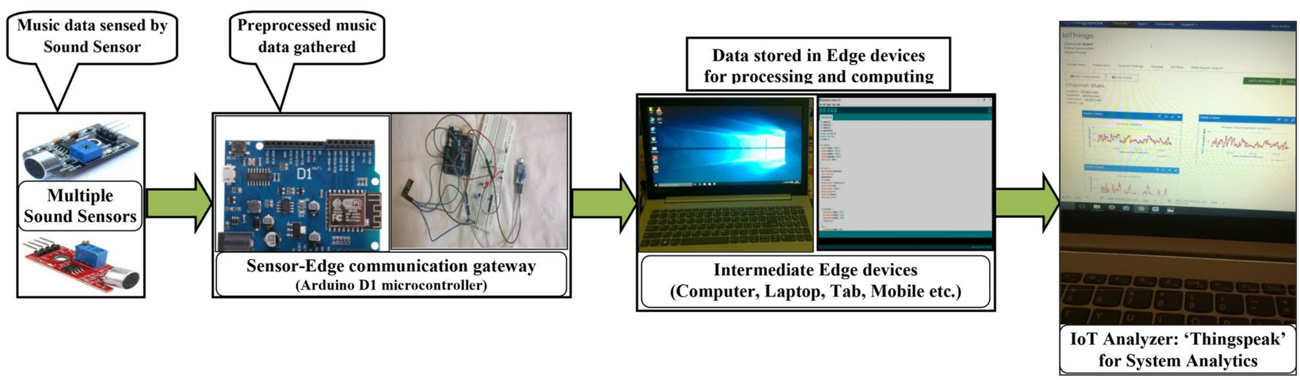

Fig. 13 Real-time system scenario of music information fusion architecture modeling in the context of Internet of Things

Table 3 Three different system archetypes for analysing and comparing the entropy

System archetypes	Information sensed from	Information sensing devices	Storage devices	Computational Environment	Additional Remarks
Archetype 1	Physical sources	Multiple sound sensors	Edge devices	Edge devices	----
Archetype 2	Physical sources	Multiple sound sensors	Edge devices	Cloud data centres	----
Archetype 3 (Proposed paradigm)	Physical sources	Multiple sound sensors	Edge and IoT analysing devices	Intermediate Edge Device	Pre-processed data stored in edge storage and after computation, data are stored in IoT analyser

and secure with its own features in a proper harmonic way.

ii. Sometimes we need to get rid of various data which aren't so very useful to us but still it occupies some space which could have been allocated to much more useful data by which we can make our system more efficient. But to detect this we again use our strategy, let's assume one data has a very high rating in volume, velocity, value but it's validity rating is so low which means that the data is too old to use or may be its newer version is available, that is when we can decide whether to put the old data in our system or not. This can be done by comparing other variables too and making some specific conditions while filtering. Thus we can make our system efficient.

iii. Having so many variables which classify the data into so many categories means the uncertainty of the system is so high thus making the system more stable. But still as we use the simple algorithm to store data as discussed in above paragraph we can still easily achieve our required data with minimum effort.

6 Comparative analysis

This section illustrates a comparative exploration of system entropy analysis in three diverse edge computing paradigms for music data fusion environments. As per the earlier discussions in subsection 5.4 on proposed system entropy, we state that system entropy can be measured by three essential components such as service latency, power consumption by the system and system temperature which are already discussed in subsections 5.1, 5.2 and 5.4 respectively. The foremost strategy behind the use of proposed methodology is to consume low power (Mukherjee et al. 2016), low service latency (Roy et al. 2018) and less system entropy in IoT devices. A real-time system scenario of proposed music information fusion architecture is demonstrated in Fig. 13 in IoT context. Based on the operational characteristics of three different archetypes, the projected comparative analysis of the system is stated in Table 3.

6.1 Measures of system entropy of three edge-cloud based system scenarios

In this subsection, the measures of system entropy of three different archetypes such as H_{sys}^{edge}, H_{sys}^{cloud}, and H_{sys}^{IoT} are analysed. The system entropy analysis are as follows:

Archetype 1 (Measure of H_{sys}^{edge}):

Let us assume that the system entropy for archetype 1 is denoted as H_{sys}^{edge} and it can be expressed as:

$$\text{Edge System Entropy, } H_{sys}^{edge} = W_{Total}^{edge} \times \Gamma_{service}^{edge} \times log_{10}(T_2^{edge} - T_1^{edge}) \tag{41}$$

where, W_{Total}^{edge} denotes the total power dissipation of the system that is defined as:

$$W_{total}^{edge} = [(W_{edge\_trans} \times R_{amt\_\exp}^{edge}/R_{exp}) + (W_{edge\_rcv} \times R_{amt\_imp}^{edge}/R_{imp})] + W_{edge\_import} \times [(L_{edge}/P_{edge}) + (N_{D_1}/V_{edge})] + [T_{D_1} \times W_{D_1}] \tag{42}$$

where, $R_{amt\_\exp}^{edge}$ symbolizes total amount of data packets transmitted to edge devices from physical sensor devices on data export and $R_{amt_imp}^{edge}$denotes data amount receives during data export in the edge storages. Rests of the parameters are described in Table 1. $\Lambda_{service}$ is the service latency that is defined in Eq. (25). T_1 denotes temperature of source sensor device andT_2 signifies the system temperature that is the computational edge device which are discussed in Eq. (35).

Archetype 2 (Measure of H_{sys}^{cloud}):

Let us assume that the system entropy for archetype 2 is denoted as $H_{sys}^{cloud}$and it can be expressed as:

$$\text{Cloud System Entropy, } H_{sys}^{cloud} = W_{Total}^{cloud} \times \Gamma_{service}^{cloud} \times log_{10}(T_2^{cloud} - T_1^{cloud}) \tag{43}$$

where, W_{Total}^{cloud} denotes the total power dissipation of the system that is defined as:

$$W_{total}^{cloud} = [(W_{edge\_trans} \times R_{amt\_\exp}^{cloud}/R_{exp}) + (W_{edge\_rcv} \times R_{amt\_imp}^{cloud}/R_{imp})] + W_{edge\_import} \times [(L_{edge\rightarrow cloud}/P_{edge}) + (P_{edge}/I_{IoT})] + [T_{D_1} \times W_{D_1}] \tag{44}$$

where, $R_{amt\_\exp}^{cloud}$ symbolizes total amount of data packets transmitted to cloud from intermediate edge devices on data export and $R_{amt\_imp}^{cloud}$ denotes data amount receives during data export in the cloud data center. Rests of the parameters are described in Table 2. $\Lambda_{service}$ is the service latency that is defined in Eq. (25). T_1 denotes temperature of source sensor device and T_2 signifies the system temperature that is the computational edge device which are discussed in Eq. (35).

Archetype 3 (Proposed archetype, Measure of H_{sys}^{IoT}):

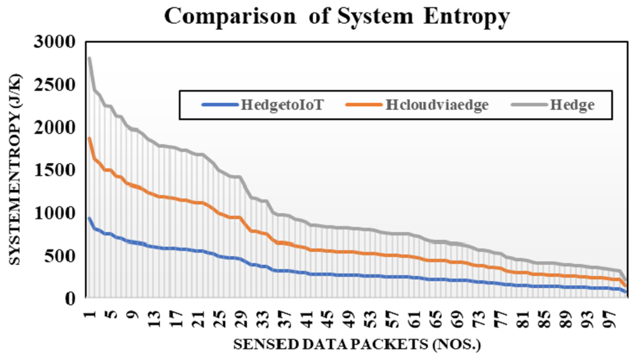

Fig. 14 Comparative analysis of system entropy against number of data packets in three different archetypes of IoT based music information fusion architecture

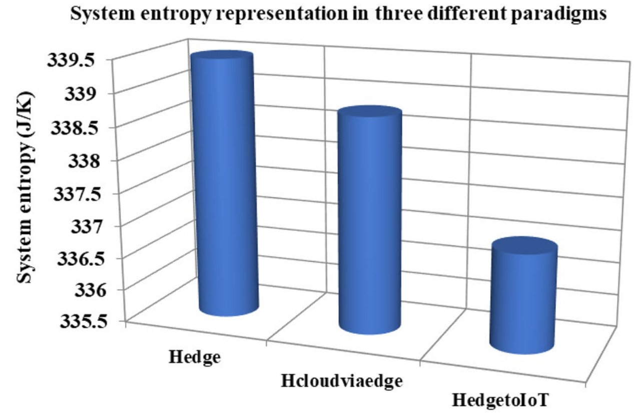

Fig. 15 Representation of Mean System Entropy in three proposed system scenarios. **a** H_{edge} (H_{sys}^{edge}); **b** $H_{cloudViaEdge}$ (H_{sys}^{cloud}); **c** $H_{edgeToIoT}$ (H_{sys}^{IoT})

Let us assume that the system entropy for archetype is denoted as $H_{sys}^{IoT}$and it can be expressed as:

$$\text{Proposed System Entropy, } H_{sys}^{IoT} = W_{Total}^{Sensor\to IoT} \times \Gamma_{service}^{IoT} \times log_{10}(T_2^{IoT} - T_1^{IoT}) \tag{45}$$

where, $W_{Total}^{Sensor\to IoT}$ denotes the total power dissipation of the proposed system that is defined as:

$$\begin{aligned} W_{Total}^{Sensor\to IoT} = & [\{(W_{edge\_trans} \times R_{amt\_exp})/R_{exp}\} \\ & + \{(W_{edge\_rcv} \times R_{amt\_imp})/R_{imp}\} \\ & + W_{edge\_import} \times \{(L_{R\_edge\to IoT}/P_{edge}) \\ & + (N_{D_1}/I_{IoT})\}] + (T_{D_1} \times W_{D_1}) \end{aligned} \tag{46}$$

where, all the parameters used in the Eq. (46), are already discussed in Table 2.

Figure 14 presents comparative analysis of system entropy in three distinct computational environments of multi-sensor based IoT archetypes for music fusion that is proposed in this paper.

6.2 Analysis and discussion

Archetype 1 illustrates that pre-processed or unprocessed music data are sensed by participated sensors, stored in the edge computing devices, and all computational tasks are fulfilled in the edge computing devices. Equation (41) depicts that in archetype 1, mean system entropy H_{sys}^{edge} for 100 transmitted data packets by the sensor devices is 339.4731825 JK^{-1}.

Archetype 2 describes that data sensing are performed by the sensors and locally stored in edge devices. All computational tasks over sensor data are done explicitly in the edge computing devices. Furthermore, processed data are offloaded to the cloud data centre for computations and storage purposes. Equation (43) depicts that in archetype 2, mean system entropy H_{sys}^{cloud} of 100 data packets is 338.7674147 JK^{-1}.

Archetype 3, our proposed paradigm, illustrates that multiple sensors sense the data and stored them locally into the IoT analysing layer after successful processing of the sensor data. All computational activities are made in the intermediate edge computing devices and pre-processed fusion-based computations are exported in the IoT analysing layer. Archetype 3 can also be demonstrated in such a way that, if all the active edge computing devices are resourceful, then pre-processed sensor information will unswervingly be transmitted to the IoT analysing layer. Computational infrastructures are provided by proposed IoT analysing layer. Equation (45) depicts that in Archetype 3, mean system entropy H_{sys}^{IoT} of 100 data packets by the systems is 336.9803687 JK^{-1}.

We have observed in Figs. 14, 15 and Table 4 that our proposed system, demonstrated in archetype 3 in terms of system entropy analysis in humanized music information fusion strategy in IoT environment reduces the system entropy or disorder of the entire IoT system than predefined and conventional approaches discussed in archetypes 1 and 2. By decreasing the system latency, device-to-device data transmission latency, we can reduce more power dissipation of the system and hence, therefore, the corresponding system entropy can also be reduced over time.

In the proposed endeavour, the participated edge computing devices and public IoT analysing tool are elected initially. We are arguably appealing that the less distances among IoT devices of every layers will reflect less service latency and power dissipation of the proposed information fusion archetype. Hence, in this projected recommended computational environment, we have proposed three dedicated layered archetypes. In IoT-based music fusion architecture, a

Table 4 Comparison table of system entropy evaluation of three different archetypes

Parameter for comparison	System Scenario vs Performance metrics	Real-time system scenarios		
		H_{edge}	$H_{cloudviaEdge}$	$H_{edgetoIoT}$
System Entropy (JK^{-1})	Data packets 01–20	127.1675857	126.8103638	125.7421979
	Data packets 21–40	201.9752274	201.5361656	200.1942499
	Data packets 41–60	269.9384087	269.3518646	267.7258697
	Data packets 61–80	425.7583297	425.0830064	422.9822357
	Data packets 81–100	672.5263612	671.0556733	668.2572906
Mean System Entropy (JK^{-1})	Total data packets: 100 nos	339.4731825	338.7674147	336.9803687

user can access and share all processed musical information within the devices in a shared network. The decisions and ratings provided by AI manager in the proposed V-schema, which are illustrated in sub-Sect. 5.7, store the information in the cloud storage finally. And end-user can also demand more data from the musical data sources for augmented fusion music composition. This proposed information fusion architecture along with proposed V-schema carries out the novelty of projected scheme in the context of IoT. The originality of the recommended strategy on music information fusion consequence is depicted in Fig. 15 in terms of the analysis of the system entropy.

7 Conclusions and future scope

An inclusive description on mobile edge computing based humanized music information fusion architecture is provided with system performance metrics to enhance computational effectiveness of the proposed system. Diverse musical elements frequently from different musical genres are assembled to denote a music-piece which capture the attention of the listeners in a different genre of music. Projected method delivers a platform to share the composed music among the listeners for enhancing level of satisfaction. In this proposed paradigm, the end-users can also access processed musical data from the cloud to compose fusion music as listeners' preferences. Moreover, this proposed paradigm could positively augment the benefits of the real users in terms of less computational costs, improved system performance, huge storage capacity, enhanced information reliability and device independence. We have documented distinctive topographies for music data fusion schema and analyzed the projected system in terms of service latency, power dissipation, system stability, information and system entropy. Our observation on the projected case-study is that information and system entropy of real-time music information fusion schema in IoT environment are significantly lower than the system entropy of conventional computing architecture. The proposed music big data architecture in IoT-based humanized music fusion prospect, described in this paper, comprises an emerging originality and to the extent that authors are aware, this is the first sound and data oriented ambient IoT analytics on humanized music information fusion architecture. Eventually, some of the research scopes which can be explored for the further extension of the proposed work are as follows: (1) Multilevel sensor information fusion for integrating and fusing multisensory data to enhance system robustness and flexibility; (2) Adaptive multisensor data fusion for finding exact information of the sensed environment; (3) Methodical analysis of information transformation; (4) Technical infrastructures for automated information fusion schema; (5) Potential decision-making circumstances for adopting information fusion systems.

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