Smart Learning Environments

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Learning analytics for IoE based educational model using deep learning techniques: architecture, challenges and applications

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Abstract

The new generation teaching-learning pedagogy has created a complete paradigm shift wherein the teaching is no longer confined to giving the content knowledge, rather it fosters the "how, when and why" of applying this knowledge in real world scenarios. By exploiting the advantages of deep learning technology, this pedagogy can be further fine-tuned to develop a repertoire of teaching strategies. This paper presents a secured and agile architecture of an Internet of Everything (IoE) based Educational Model and a Learning Analytics System (LAS) model using the concept of deep learning which can be used to gauge the degree of learning, retention and achievements of the learners and suggests improvements and corrective measures. The paper also puts forward the advantages, applications and challenges of using deep learning techniques for gaining insights from the data generated from the IoE devices within the educational domain for creating such learning analytics systems. Finally a feature wise comparison is provided between the proposed Learning Analytics (LA) based approach and conventional teaching-learning approach in terms of performance parameters like cognition, attention, retention and attainment of learners.

Keywords: Deep learning, Internet of everything (IoE), Twofish, Software defined networking (SDN), LSTM, LAS

Introduction

Since the inception of 'Internet of Everything (IoE)' technology, the computing paradigm has totally transformed. New tools and techniques are being devised to handle the varied nature of the voluminous big data generated from the ubiquitous IoE devices. IoE is already exhibiting signs of completely transforming the lives of human beings (Jara et al., 2013; Ashton, 2009; Miraz et al., 2015). A typical IoE system is a collection of large number of devices which are wirelessly connected with each other and the base station. These devices are embedded with micro-chip based sensors, actuators and transponders for performing the task of sensing, storing and forwarding the information about themselves and their surroundings (Jara et al., 2013; Ashton, 2009; Miraz et al., 2015). The different devices in the IoE ecosystem are generally of different make and model which usually stores unstructured data. Therefore there is a vital need of standardizing the data captured by these devices so as to convert it into a common standard format. Furthermore, since the data captured by these devices mainly travel through the wireless medium, it becomes necessary to protect the data in order to maintain its confidentiality. The sensor carries large amount of data which when analyzed in a correct way can give better insights that can be useful in taking well informed and precise decisions. Today, deep learning is considered one of the most prominent technique for performing state-of-the-art classification, analysis and predictions (Du & Swamy, 2013; Chapelle et al., 2009; Zhu & Goldberg, 2009; LeCun et al., 2015). This paper presents an IoE based Educational model and discusses the applications, advantages and challenges of using deep learning techniques to develop a learning analytics system by effectively using the IoE big data for taking better and efficient decisions within the educational domain.

Deep learning is a part of machine learning technique based on learning data representations. This learning can be unsupervised, supervised or semi-supervised (Du & Swamy, 2013; Chapelle et al., 2009; Zhu & Goldberg, 2009; LeCun et al., 2015). In other words we can say that, any deep learning model learns from the experience with minimal external interference. In a typical deep learning system, a computer model is created which is capable of performing the task of classification on the basis of input images, audios and videos. The training of these models is conducted using deep neural network architecture and huge datasets which are generally labelled (Du & Swamy, 2013; Chapelle et al., 2009). Figures 1 and 2 presents the traditional machine learning approach and deep learning approach respectively for performing the task of classification.

Related work in brief

This section presents some of the related work in brief. The authors in (Warburton, 2003) reviewed the factors affecting the process of deep learning for performing learning analytics and suggested ways to adopt deep learning strategies among students. The authors of (Luna Scott, 2015) talked about the new pedagogies for the twenty-first century wherein they showed the importance of project based and problem based learning techniques. The authors of (Gul et al., 2017) presented a review work wherein they discussed about the challenges and future directions of IoT in the field of education. The researchers in (Chotitham et al., 2014) discussed the effect of deep learning on the achievements of the students of “Chulalongkorn University”. Golino et al. (Golino et al., 2014) discussed about combining the psychometric and machine learning techniques and its implications to predict the academic achievements of the students. The authors of (Zhang et al., 2016) talked about incorporating “Deep belief Networks (DBN)” and feature engineering to solve the task of “automatic short answer grading (ASAG)” system. Smith et al. (Smith et al., 2015) introduced diagrammatic student model to predict the attainment of concept on the basis of the sketches using deep learning concepts. The researcher of (Nouby & Alkhazali, 2017) investigated the effect

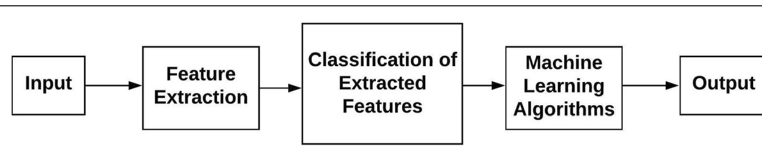

Fig. 1 Traditional Machine Learning Approach. Highlights the steps followed in traditional machine learning approach. For the given input first, the relevant features are extracted, then these features are classified and finally machine learning algorithms are applied on them to perform the task of object classification

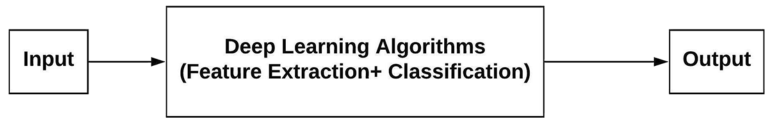

Fig. 2 Deep Learning Approach. Presents the deep learning approach of object classification. Here the feature extraction and classification task are done simultaneously

of blended learning environment on the attainment of the students of "Arabian Gulf University". The author in (Rodriguez, 2009) studied the impact of academic "self-concept" and "outcome-expectations" for choosing the learning strategy considering the academic achievement as a primary goal. The Hewlett Foundation (VanderArk & Schneider, 2012) suggested that deeper learning helps in enabling the students to be proficient in the core academics, think critically, work in groups and promotes self directed learning. Angel Fidalgo et al. (Fidalgo et al., 2014) developed a learning Analytics system to analyze the intra group interactions in order to evaluate the work competence of the groups in a university education system. The authors in (Greller & Drachsler, 2012) proposed the visualization of twitter usage by the student for performing the learning analysis using R programming. The researchers in (Dyckhoff et al., 2012) discussed about a generic design framework for establishing a learning analytics system in order to promote quality teaching and learning. They also discussed the various limitations of the learning analytics system. The researchers in (Poon et al., 2017) talked about a toolkit name "eLAT" for performing the task of learning analytics. The "eLAT" is capable of graphically indicating the learner behaviour, assessment and feedback in order to facilitate inclusive teaching and suggests improvements. Poon L K M et al. in (Uskov et al., 2017) discussed about using the logs of LMS to analyse learning capabilities and achievements of online learners using data mining and visualization techniques. Uskov V.L et al. in (Kovanović et al., 2017) provided a detailed analysis and conceptual design of smart learning analytics for smart university. The author in (Linda, 2014) presented a new model for performance analysis of the students using "automated learning analytics techniques". Their model claimed to provide real time cognitive development monitoring and feedback mechanism for the students. Linda A. (Papamitsiou & Economides, 2016) talked about the application of predictive healthcare analytics. The paper provided seven ways in which predictive analytics can improve healthcare. The researchers in (Rienties et al., 2017) suggested a theoretical framework for the assessment mechanism of the learners by the instructors. The authors in (Xhakaj et al., 2017) discussed about the effects of exploiting learning analytics model on the "attitude, behaviour and cognition" of the learners. They further discussed the usage of (LA-IEF) at the "open university UK". Xhakaj F. Et al. (Akhtar et al., 2017) analyzed the usage of LUNA ("a dashboard prototype") and its effects on students and teachers. Akhtar S et al. (Healion et al., 2017) reported the usage of "Computer Support Collaborative Learning environment" in teaching CAD in laboratories. The researchers in (Atherton et al., 2017) discussed the importance of tracing the physical movements to be incorporated in the learning analytics in order to achieve better understanding of in-class activities. Mirella Atherton et al. (Tempelaar et al., 2018) conducted the study aimed at finding the correlation between the online study approach and its positive effects on attainments of the learners. Dirk Tempelar et al. (Ravi et al., 2017) provided an empirical study aimed at showcasing how "learning decomposition data" can be used to deliver better "learning interventions". D Ravi et al. (Walker, 2012) proposed a methodology using the deep learning techniques to capture sensor data and perform analysis to predict real time activity classification. Furthermore in order to refine the approach, spectral domain pre-processing was incorporated in their approach.

Architecture of IoE based educational model

In the proposed architecture, the stakeholders (students, teachers, staff members, management members, parents etc) and other important entities like Library, Entry-Exit Gates, Canteens, Auditoriums, Laboratories, Washrooms, Classrooms, Gymnasiums etc. within the educational system premises are embedded with several microchip based wireless sensors, actuators and transponders using wearable and or fixed devices. The sensors in these devices sense and capture the information about themselves and their surrounding environment and send it to the base station (or sink) for further processing. These sensors produce a huge amount of data which travels from source to destination and vice versa using a wireless medium, therefore in order to secure this data, we propose to encrypt the data using Twofish Cryptographic technique (Whiting & Schneier, 1998; Schneier et al., 1998; Schneier et al., 1999). Furthermore to ensure optimal use of bandwidth and faster data transfer, the concept of Software Defined Networking (SDN) (Xia et al., 2015; Braun & Menth, 2014; Kreutz et al., 2015) has been incorporated in our approach. Finally, in order to perform better analytics and predictions using the data received from these sensors, deep learning techniques have been used. Figure 3 presents the overview of the architecture of the proposed approach.

Technical work flow of the proposed architecture

Every entity and stakeholder in the proposed model is embedded with multiple sensors which captures the information about itself and its surroundings. Each of these sensors transfers this information to the Data Encryption and Standardization Unit (DESU) for further processing. The DESU first converts the captured data (which is largely unstructured) into a standard format and then passes it to the Encryption sub-unit for converting it into secured format. There are several steps followed in standardizing the raw data captured by the sensors. These are given below.

1. *Data Source identification and Authentication*: Since there are large numbers of sensors involved, it is pertinent to know the legitimacy of the data source in order to avoid any security issues. Every sensor has a pre-identified number, which can be identified and cross-checked at the DESU
2. *Data size and type identification:* It is also very important to know about the type and size of the data captured by the sensors. The DESU is equipped with data-type and data-size identifiers which readily identifies which type of data is captured by the sensor along with its size.
3. *Choosing data Standards:* The most important part of data standardization process is the identification of the correct format of the data. Since all requests are not similar, they must be handled in different ways and thus choosing a right data standard for storing and servicing the right type of request is an imperative decision.

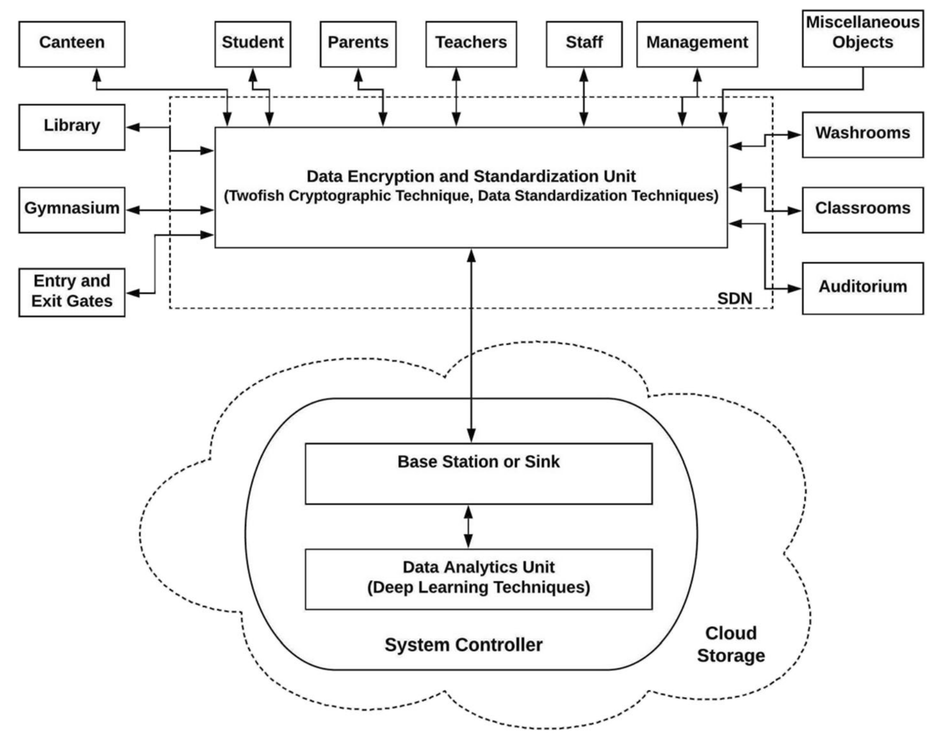

Fig. 3 Architecture of IoE based Educational Model. The architecture consists of various components of the proposed IoE based Education Model. The system controller is the brain of the system which is responsible for coordinating all the activities within the system

4. *Data Cleaning:* It is a process of removing noise, data outliers and other non-relevant sections from the captured data.
5. *Data Normalization:* In this process, the data is restructured so as to remove redundancy and improve data integrity.

After completing the above steps, the raw data from the sensors is converted into a standard format. After this, the formatted data is passed onto the encryption unit for converting it into a format which is identifiable and accessible only by authorized personnel using the Twofish cryptographic technique (Whiting & Schneier, 1998; Schneier et al., 1998; Schneier et al., 1999). Since Twofish is a symmetric key cryptographic technique, we need only one key for its encryption and decryption. Figure 4 shows the building blocks of the Twofish algorithm.

There are several reasons for incorporating Twofish cryptographic technique in our approach like its support for variable length key sizes, highly secure and fast execution, support for varied encryption modes, compatibility with microchip based smartcards and other miniature hardware types etc. For further details about Twofish algorithm, one can see (Whiting & Schneier, 1998; Schneier et al., 1998; Schneier et al., 1999).

After the data is encrypted, it is forwarded to the base station (or sink) on the cloud for storage and taking appropriate decision by the system controller. The system controller in consultation with the data-analytics unit analyzes the requests from the users and instructs the devices to perform the requested operations in an intelligent and learned way. The data transfer from one unit to another is governed by SDN controller

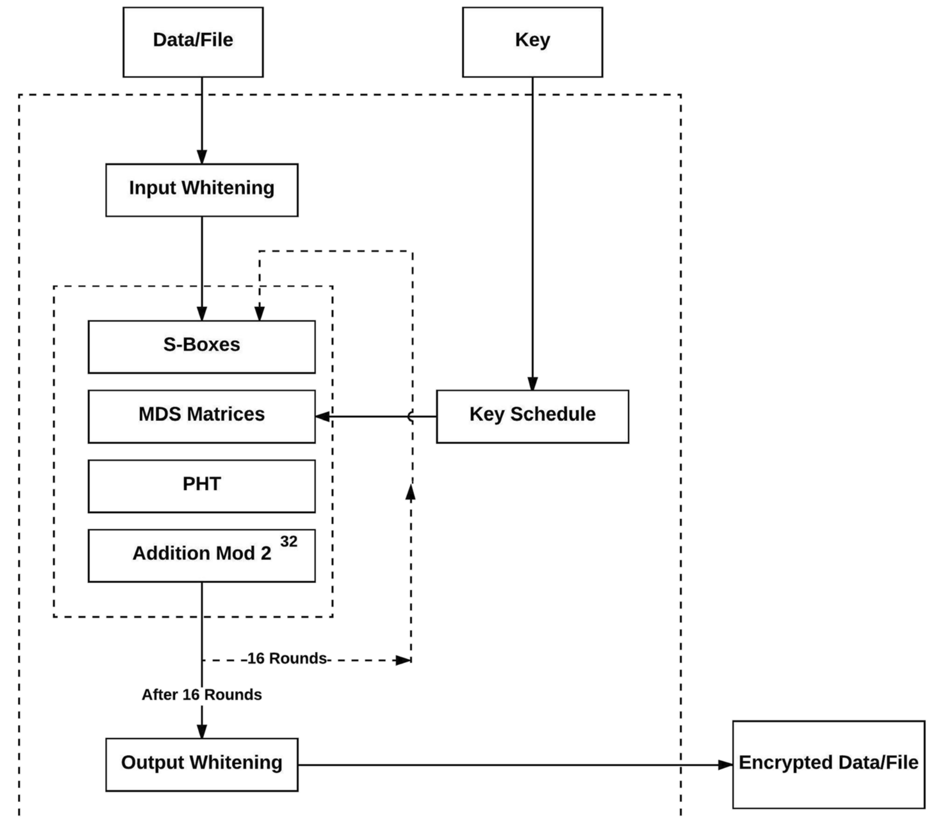

Fig. 4 Building blocks of Twofish Algorithm. The data gets converted into the encrypted form by passing through the building blocks of Twofish cryptographic technique

which dynamically selects the most appropriate path for data transfer on the basis of the real time network traffic inputs. SDN controller is also capable of managing the network traffic, bandwidths and topologies in real time as and when required (Xia et al., 2015; Braun & Menth, 2014; Kreutz et al., 2015).

In a typical IoE ecosystem some of the requests are user centric while others are object or conditions centric (which require little or no human intervention) (Maksimović, 2018; Bayani et al., 2017; Bagheri & Movahed, 2016; Benson, 2016; Sethi & Sarangi, 2017). For such requests, deep learning techniques can play a pivotal role in enhancing the training of the system for improving the precision of the device's responses in servicing the requests. Figure 5 shows a simulation of the typical components in an IoE based classroom setup (created using Cisco Packet Tracer 7).

Learning analytics using deep learning techniques

Learning analytics may be defined as the collection of data and information about the learning patterns, retention capabilities and attainment of the learners so as to improve and optimize their learning and retention capabilities (Siemens, 2013; Analytics, 2017). The retention capabilities of the brain are governed by the formation of short term and long term memory. If we are able to successfully transfer the "short term memory (STM)" to "long term memory (LTM)" we can retain the learned things for a longer

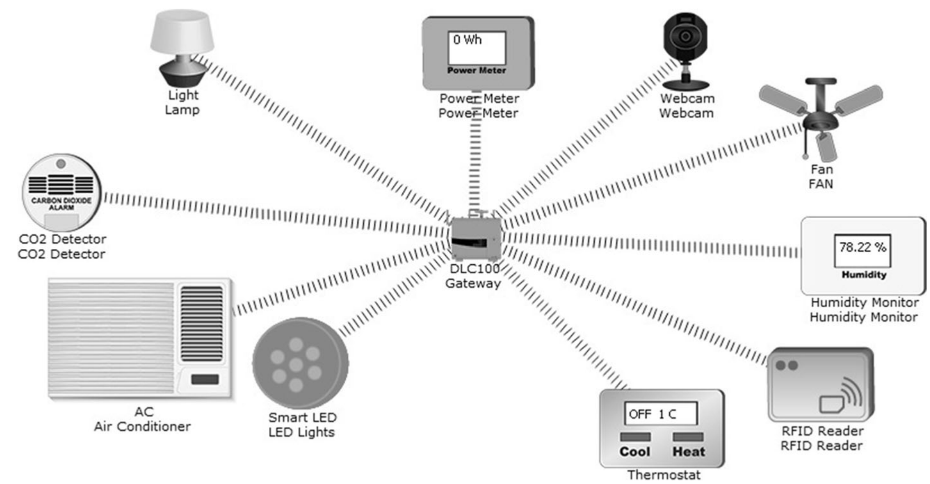

Fig. 5 Components in IoE based Classroom Setup. The various components are simulated using Cisco Packet Tracer Software. The dashed line connecting the components and gateway represents wireless connection

period of time. The conversion of STM to LTM is done in several stages and is largely because of the synthesis and degradation of certain kind of synaptic proteins available in the brain (Fioravante & Byrne, 2011). With deep learning we try to further fine tune the insights about the data, learning and behavioural patterns that were not possible with the traditional machine learning techniques in order to improve the accuracy of the results. The insights thus obtained can be used to trigger portions of brain in order obtain longer retention capabilities (Fioravante & Byrne, 2011). Figure 6 shows the overview of the learning analytics model for students based on deep learning techniques.

By following the steps (in sequence) as shown in the model in Fig. 6, we can create a learning analytics system for the students. The LAS algorithm given below presents the steps for creating a learning analytics system. The learning analytics model presented here make use of Long-Short Term Memory (LSTM) network.

Algorithm: LAS Algorithm

1. Inputs:
   a. Data from learners and IoE devices
   b. Request from the user/learners
2. FOR each data element, DO
3. Identify the relevant portions among the data
4. Remove irrelevant portions (data outliers, missing values etc) from the data
5. Feed the data into the LSTM network for training
6. Identity the request and its type
7. Feed the request into the LSTM network
8. Identify key points among the data with respect to the request type
9. Perform the analytics on the data (Data Processing)
10. Produce the Result (or Service the request)

Some of the other applications that can be created using the proposed learning analytics model are highlighted here (Ark, 2015; Brownlee, 2016).

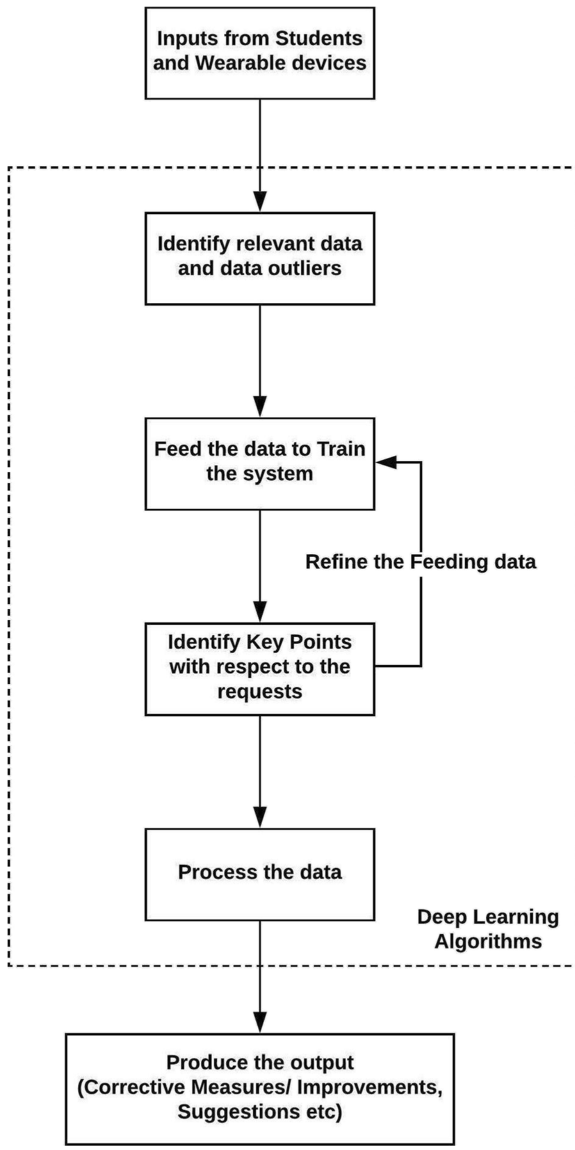

Fig. 6 Proposed Learning Analytics System Model. The various steps and components involved in creating the learning analytics model

1. *Content Analytics:* Deep learning techniques can be used to create content analytics to dynamically restructure and optimize the content modules as per the need of the students. With this, it will be easier to track the learning of students and suggest measures for further improvements. Furthermore it is often observed that the test formats has a direct impact on the strategy of performing the study by the students. With deep learning techniques, we can device novel and formative test formats and challenge the students to come up with new techniques and strategies to study for such startling formats. This approach enhance the thinking capabilities, cognitive ability and retention among the students thus making them thrive in academics (Ark, 2015; Brownlee, 2016; Fullan & Langworthy, 2013; Kolb & Kolb, 2005; Baeten et al., 2010). Figure 7 Presents the overview of the system for getting customized learning/study plan for students.

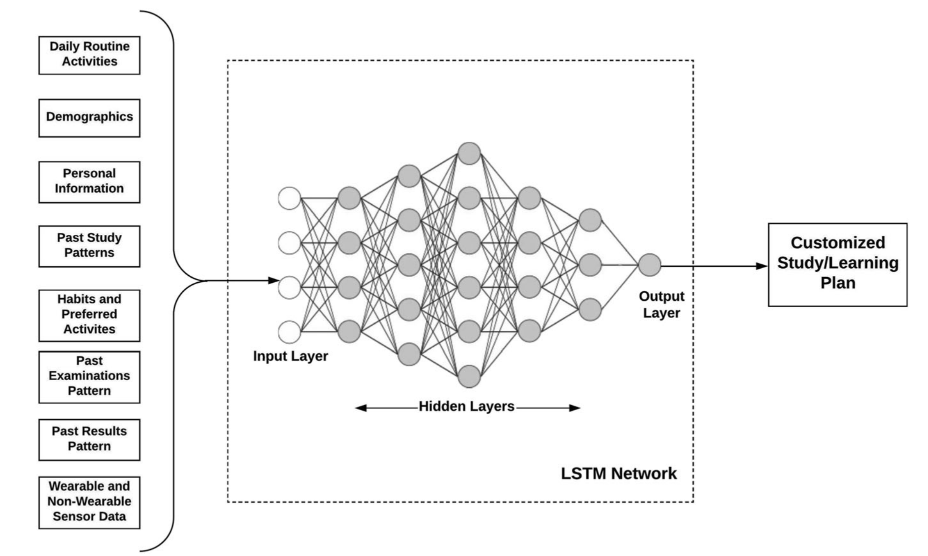

Fig. 7 System for getting Customized learning plan. The multiple user input is passed to the LSTM network for processing and the outputs gives the customized learning plan

2. Similarly we can create a system for getting the customised lecture plan of the teachers for a particular group (class) of students. Figure 8 gives the overview of the system.
3. *Adaptive learning strategies or game based learning strategies:* These can be adopted on the basis of the continuous inputs from the students and observations of the teachers.
4. *Teaching-Learning Gap Analysis:* On the basis of past and current (instantaneous) data of the teaching and learning behaviours of teachers and students, the

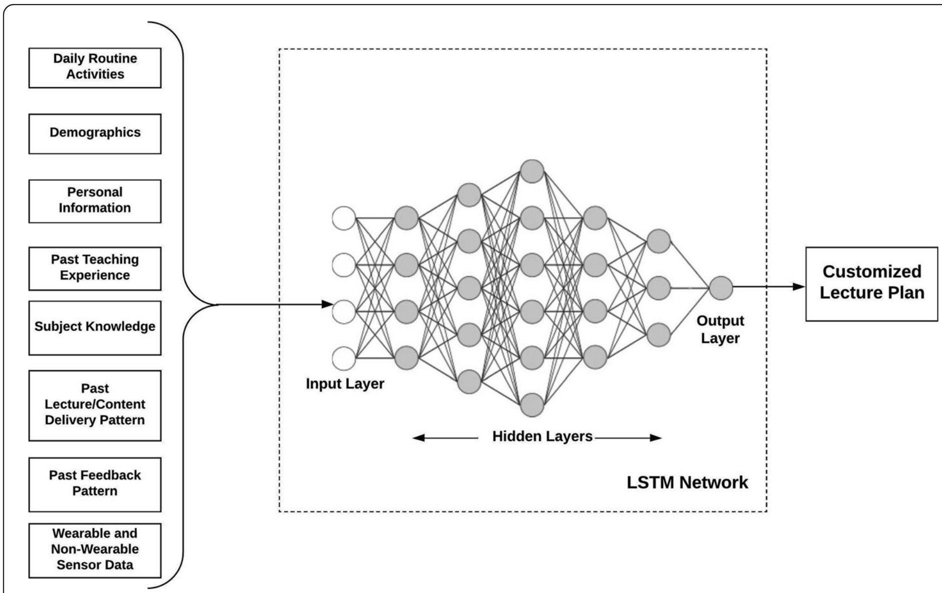

Fig. 8 System for Customized Lecture Plan. The multiple inputs from the teachers are passed to the LSTM network for processing and the outputs gives the customized teaching plan

Teaching-Learning gap analysis can be observed and corrective measures can be adopted to improve the overall teaching-learning process.

5. *Customized Teaching-Learning strategies:* By using deep learning algorithms, we can train the system to process the inputs from the students and teachers to suggest customized teaching-learning strategies applicable to different classes of students.

Advantages of the proposed approach

The proposed system can be adopted to exploit the advantages of the latest innovations and technologies in an IoE ecosystem tailored for the educational domain. Some of these are presented below (Ark, 2015; Brownlee, 2016; Kolb & Kolb, 2005; Baeten et al., 2010).

Security and authentication

The entry and exit gates of the educational premises, classrooms, laboratories, gymnasiums, auditoriums, washrooms etc. are embedded with microchip based sensors which can let the door be opened or closed only by legitimate personnel, thus preventing any security breaches and trespassing. The entire campus premises can be monitored using the smart cameras which are capable of sensing any abnormal activity (thefts, harassments, disasters etc) and report to the control station in real time.

Reduced power consumptions

The educational premises including the classrooms, staff rooms, laboratories, library, gymnasium etc. are equipped with smart HVAC and electrical systems for optimal consumption of electricity. The embedded sensors within them can monitor the temperature, pressure, humidity and other parameters within the premises and can dynamically adjust to the atmospheric conditions and control the electrical appliances as per the preferences of the users. This technique will ensure less carbon emission which can be helpful in preserving the environment to a certain extent.

Student and staff attendance management

The classrooms and laboratories are equipped with auto attendance tracking unit which reads the sensor data from the student's identity card and marks their attendance. The same attendance of the students gets reflected in the teacher's account. The attendance tracking unit is also capable of sending the notifications to the students and their guardians in case their attendance is below the threshold value at any point of time. The teachers can also manage and keep track of their employee-leave status. With this, the students and staff can keep track of their attendance in a much easier and simpler manner and thus reducing the manual paper work.

Smart teaching and learning activities

The new generation teaching pedagogy is not confined to books and lectures notes only. The innovations in technology have opened doors for using varied sources for teaching and learning. We can use YouTube, Twitter and Open Courseware etc. for getting lectures of various eminent Universities and colleges. Apart from that, the classrooms are equipped with sensors based smart HVAC systems which can be helpful in making conducive teaching-learning environment by maintaining the desired temperature and humidity favourable for teaching –learning activities. Also the smart camera installed inside the classrooms captures the live lectures and save them on cloud for future references. The students (using their credentials) can view the lectures at their own convenience if they have missed the classroom session for any reason since the lectures are saved on the cloud which can be accessed 24X7 from anywhere. This narrows the digital divide and gives an extended learning time. It further removes the need of copying the lecture notes from the peers at later stages. Similarly the teachers can see these lectures for future references. The teachers can also give the assignment to their students using a smart online portal with a facility to evaluate the same and send a comprehensive feedback to their students. This reduces the manual work and increase the efficiency of the teachers and well the students. The virtual lab setup can be used to give practical training of the concepts. The learners can use any hand held device or laptops to access these labs using basic internet connectivity. This can drastically reduce the cost incurred in purchasing equipments, machine, computers etc. for lab setup and at the same time reduces the physical space requirements also.

Health and hygiene

The sensors embedded in the canteens are capable of identifying the eating habits of an individual and make meal suggestions accordingly. The calorie meter embedded in the wearable device of the teachers, staff members and students keeps track of their calorie intake and suggests the best suited meal menu according to their past calorie intake. These sensors also monitors the vitals of the person and notifies them in case of any abnormal variation (activity) is observed. This will help them to continuously monitor and keep track of their health and hygiene.

Automated library management

All the books, journals, manuscripts in the library are equipped with sensors/RFID tags. The students who want to issue any book just need to scan the book tag and the entry of that book will be inserted in their personal record along with the due date of return. This will reduce the manual entry at the book issuing counter of the library and thus save man-hours and man-power both. Furthermore with the presence of digital media, the role of conventional textbooks is limited to classroom teaching only. The students and teachers can use the omnipresent digital media 24X7 from anywhere at any time thus expanding the horizon of learning and removing the barrier of classical teaching methodologies.

Challenges in adopting the proposed approach

The challenges of the proposed architecture can be among the following (Jara et al., 2013; Ashton, 2009; Dyckhoff et al., 2012; Madaan et al., 2017):

- *Cost of IoE infrastructure:* The cost involved in setting up of the proposed IoE architecture can be a major overhead in its implementation in small educational institutes.
- *Varied data formats:* The ever changing technology of sensors which captures huge amount of data by the multiple means is largely in different formats.

- *Very high velocity of data generation:* The sensors embedded in the various participating IoE devices captures instantaneous information generated at a very fast rate. Proper storage of these data without missing any relevant part of it as well as removing the data outliers remains a challenging task for the data analysts and scientists.
- *Heterogeneous data types:* Since we have multiple devices which are generally of different make and sizes. They produce data which are in different types and sizes. The IoE system architecture should be robust and capable enough to handle heterogeneous data types
- *Security Issues:* Security remains the primary concerns when we talk about effectively handling large amount of data. The questions like "Who owns, what data at what time", and "who can access the data" should be addressed effectively in a good IoE system architecture.
- *Timely availability:* In real time applications, the timely availability, processing and presentation of data is one of the biggest challenges faced by the organizations.
- *Network latencies and failures:* Since the whole concept of IoE relies on the interconnection of large number of components in a network. The network latencies and failures are obvious.
- *Mining relevant data from the huge piles of big data:* Effective mining of relevant information is one of the primary prerequisite for constructing a good classification and prediction model. The techniques like classification, clustering, data cleaning, pruning etc. plays a vital role in this.
- *Data storage:* The architecture should be able to store the gigantic volumes of data produced by the IoE devices without compromising on the read/write efficiencies.
- *Stringent privacy protection laws:* The rigid privacy protection laws can sometimes cause hindrance in adopting the proposed approach at it involves information linkage from multiple parties, devices and systems.
- *Convention mindset and privacy concerns of individuals:* Another challenge for the proposed approach can be the conventional mindsets of the users which never want themselves to be monitored citing personal privacy and other similar factors.

Applications of the proposed approach

With its ubiquitous nature and scalable architecture, IoE is finding its applications in almost every domain of human life. Deep learning techniques can be helpful in attaining deeper insights about the data and applications which in turns can be used for creating better software, tools and systems for the wellbeing of the humans. Apart from learning analytics, the general applications of proposed deep learning based IoE Architecture can be among the following (Yaron, 2017; MathWorks, 2017; Schmidhuber, 2015; Najafabadi et al., 2015):

Text to speech and speech recognition system

With effective deep learning techniques we can construct systems which are capable of recognizing the voice in a best possible way like never before. These systems can be embedded in various devices and can be used as a password. For example: voice assisted computers, appliances, systems and equipments for differently-abled persons, passwords in mobiles, computers and other electronics devices (Yaron, 2017; MathWorks, 2017; Schmidhuber, 2015; Najafabadi et al., 2015).

Image and language translations

Deep learning algorithms make it possible to instantly convert any language to any other language. These systems primarily work on the concept of machine translations. This is particularly helpful in situations where a non native person can understand and speak the native language in real time. These can be helpful in promoting educational exchange programmes as such system will remove the language barrier among the students and teachers of different countries (Yaron, 2017; MathWorks, 2017; Schmidhuber, 2015; Najafabadi et al., 2015).

State-of-the-art Behavioural systems

They are those systems or components which learn from the behaviours. The best examples of such system are Self-Driven Cars, Automated drones, Smart Homes, Smart Transportation Systems etc. These systems stores all the previously done actions of the users and acts accordingly at later stages by processing the data stored from those actions (Yaron, 2017; MathWorks, 2017; Schmidhuber, 2015; Najafabadi et al., 2015).

Predictive healthcare systems

They are the systems which are capable of predicting the conditions of a patient in near future on the basis of various inputs and data received from the sensors attached to the patient's body. They are still in their embryonic stage and if successful they can surely take the healthcare system to the new horizons (Yaron, 2017; MathWorks, 2017; Schmidhuber, 2015; Najafabadi et al., 2015).

Novel security and authentication techniques

Deep learning techniques have opened a new era of security and authentication mechanisms. Using these techniques we can construct more secure and powerful tools and techniques which can be used to protect our identity as well as other valuable information, systems and components (Yaron, 2017; MathWorks, 2017; Schmidhuber, 2015; Najafabadi et al., 2015).

Conclusion and discussions

Deep learning techniques look promising because of their baffling ability to reveal intricate formats among the data and provide novel insights to suggest improvements. This is the reason why they are finding their applications in varied computing domains. From the proposed architecture, it can be concluded that deep learning techniques are well suited for getting a student centric learning ecosystem wherein a student gets the customized learning strategy or approach as per their need and desire for better understanding and longer retention. Similarly the lecture plans and lecture delivery modes can be customized as per the understanding and interests of the students to make the task of teaching and learning more fruitful. Table 1 presented here shows a feature wise comparison of the proposed Learning Analytics based Teaching-Learning approach and conventional Teaching-Learning approach.

It is evident from Table 1 that the learning analytics based approach fares much better as compared to conventional learning approach in terms of holistic progress, cognition, attentiveness, retention and attainment of the learners.

With deep learning techniques as a tool, we can train the system in a much more effective way and have better results as compared to traditional machine learning

Table 1 Comparison of Conventional and Learning Analytics (LA) based Teaching-Learning Methodologies (LeCun et al., 2015; Warburton, 2003; Luna Scott, 2015; Gul et al., 2017; Chotitham et al., 2014; Nouby & Alkhazali, 2017; Rodriguez, 2009; VanderArk & Schneider, 2012)

Parameters	Teaching-Learning Methodology	
	Conventional Method	Proposed Learning Analytics (LA) based method
Learning Time	Fixed	Increased Learning Time with 24X7 availability of teaching learning resources
Attention span	Very short	Fairly Large as it involves the learner throughout the process
Understanding ability	Limited	Learners are able to understand much better
Interaction	Limited interaction (limited only in classroom)	Enhanced and expanded interaction among peers and with instructors
Evaluation and Feedback	Prefixed evaluation system and Limited or No Feedback provision	Continuous evaluation with Formative and Elaborative Assessment and comprehensive Feedback mechanism
Motivation	Depends on Instructor	Learners are Self Motivated
Retention Capabilities	Lower	Higher as the learners are learning the concepts and applying in real life scenarios
Attainment Capabilities	Lower	Higher
Cognitive Ability	Limited	Enhanced Cognitive Abilities
Mode of Delivery	Teacher Centric	Learner Centric
Academic Independence	Learners are confined to classroom teaching and learning only	Learners are encouraged to use varied learning tools and techniques, think out of the box, and use unconventional ways of analyzing and solving problems. Focus on real life problems
Study type	In general, do not promote collaborative/group study	Promote collaborative/group study

techniques. For example, we can have a deep learning based voice recognition system wherein the system is trained using deep learning algorithms to have an exclusive voice command control over the various components of the system. This can be used by differently-abled persons to control the equipments, appliances and systems. Such systems can also be used as a password for mobiles, bank lockers, home automation system etc. We can also have domain specific feature enrichment techniques which can be used in stock markets, predictive healthcare systems, state-of-the-art security and authentication mechanisms, enhanced seismic data analytics etc. Furthermore we can create deep learning based healthcare systems for better diagnosis and treatment of the patients. If they are effectively merged with IoE technology, the result will surely be beneficial for the humans at large. Although there are certain limitations and challenges associated in implementing deep learning techniques with IoE big data as discussed in the previous section "Advantages of the Proposed Approach", however these challenges can be converted into opportunities with the development of new techniques and architectures. In the end we can say that deep learning is still evolving but it surely has great potential to further streamline the process of data classification, analysis and predictions.

Availability of data and materials

Data sharing is not applicable to this article as no datasets were generated or analysed during the current study.

Authors' contributions

MAA constructed the idea and conceptualize the designing. GT performed the leterature review and created the graphics. PA identified the key comparison between the conventional and proposed methodology. MAA, GT and PA wrote the manuscript.

Competing interests

The authors declare that they have no competing interests.

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