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Smart City Sensors for Tailored Learning Experiences

Mohammad Amir Hossain[1], Md. Adil Raza[2], Md. Hossain Al Mamun[3], Taqi Yaseer Rahman[4], Jami Yaseer Rahman[5]

[1,3]AVP, ICT Division, Union Bank PLC, Dhaka
[2]Wing Commander, BAF, Dhaka
[4]MBA, North South University Dhaka, ID: 1915103060
[5]CSE Department, BRAC University, Dhaka, ID: 22101915

Abstract

For several years, I have observed that human life seems to have entered a phase of instability, facing challenges unlike any seen in the past century. In 2019, an invisible adversary, the COVID-19 pandemic, emerged from the dark corners of the universe, bringing the normal flow of life to a halt. Its impact extended beyond health, causing global economic recessions and increasing social unrest. Alongside this came the rise of warfare and hostility, replacing compassion and unity with division. These circumstances have also posed significant challenges in the field of education, restricting opportunities for knowledge acquisition. Education is regarded as the backbone of the society. Stopping or giving a hiatus in education can have disastrous effects on the advancement and the systematic improvement and gain of knowledge in society. As such a relatively buzzing concept "IoT" can be a very demanding solution for the impasse. This paper makes an attempt to shed light on how IoT can be successfully integrated into the educational sector and at the same time discuss improving the architecture of traditional IoT-based smart education by giving more dynamism, presenting the education system in a more intelligent way that can be achieved by integrating Artificial Intelligent (AI) along with data mining technology, Deep learning, software define network (SDN) and implementing Edge computing.

Keywords: Internet of Things, IoT architecture, Deep Learning, DM, AI, AR, Edge Computing and smart classroom

1. Introduction

The rapid advancement of Internet of Things (IoT) technology and deep learning algorithms has opened new paths for enhancing educational experiences in urban environments. Corona has affected students not only in Bangladesh but also all over the world. Alternative methods are being used to keep the educational activities going. Sometimes teachers take their classes using Facebook Live or Zoom. Online virtual methods have also gained a lot of popularity **[1]**. But in the socio-economic context of our country, this advantage is not going to reach the marginal level. This problem exists not only in us but in the whole world. Schools around the world had to close quickly as the outbreak of Covid-19 spread worldwide. Although many schools were already conducting online classes according to their syllabus, most of them did not become 100% digital. Particularly out-of-town areas were deprived of this facility. IoT is helping educational institutions a lot with the limitations and valuable work of their worthless work. IoT based systems is in the teaching-learning process can facilitate and promote a higher level of personalized learning. Higher education institutions can help to track major resources, create smart lesson plans, design secure campus, enhance information access that improve the efficiency of many academic processes. The Internet of Things (IoT) is conquering the entire world by connecting various objects around us and enables interaction among people, objects and environment via artificial intelligence for education. Andreas Kaplan and Michael Henlin define artificial intelligence as the capability to precisely analyze external information, learn from it, and apply that learning to make flexible adaptations. **[2]"**

Background of IOT-based Education

Mark Weiser says, "The most profound technologies are those that disappear. They interweave themselves into the fabric of daily life until their indistinguishable from it" **[3].** Kevin Ashton first used the word Internet of Things in 1999. From the beginning, various experts have interpreted the Internet of Things (IoT) in different ways like Internet of Everything, Internet of Anything, Internet of Services, Internet of People, Internet of Signs, Internet of Data or Internet of Processes **[4].** Smart education system cover, intelligent Tutoring Systems (ITS), Web-based Learning, Adaptive Learning Systems, Technology-enhanced Learning, Context-Aware Ubiquitous Learning, Mobile Learning, using sensing technologies **[5]**. Mostly a smart Education system can be observed as a technology boosted tutoring system which enables learner to learn in the real world.

Given the current situation, online classes have become a source of hope for students and teachers, but the question remains, can it really be an alternative?

In my personal experience, taking an online class seemed to satisfy the taste of milk for the first time. Standing in front of the students and keeping an eye on them is different. Understanding how their eyes and body language made sense of what was coming out of them and understanding that would serve as a salvation in moving on to the next thing. But how much of this is possible in online classes? Yet the world is changing so we should be accustomed to accepting the change that will be useful to the students. The current education system has undergone major changes and transformations in the last few years. Technology is rapidly being used as a tool to provide new and better ways to engage students and teachers. With digital books, selective exams personalized and mobile learning making waves nowadays, the future of technology in the education industry is heavily influenced by wearable, virtual reality, location-based services and sensor technology. Traditional classrooms using blackboard, projector smart AC, Camera along with Switch, Router and cloud database serving SMS, e-mail, management portal, dashboard etc **[6].** This study aims to develop and evaluate a framework that utilizes IoT sensors and deep learning to enhance personalized, context-aware education in smart cities.

We assume that the integration of IoT sensors and deep learning will significantly advance the personalization and contextual relevance of educational experiences in smart cities.

2. Literature Review

A number of architectural journals on how to provide smart education based on IoT have been studied.

We were encouraged to this point after studying the journal "Smart Education Architecture Using the IoT Technology". This journal is written by Mr. Palanivel Kuppusamy, Pondicherry University **[7]**, 43 publications, 104 citations. In this journal, he highlights various aspects of IoT architecture and outlines some of its limitations and challenges. Another journal called "Using IoT Technology to Improve Online

Education Data Mining -Writer: Sun Yi, 10 publications, 20 citations" studied the following topics in detail.
The summery of this journal is how to use artificial intelligence technology to make education more traditional through online virtual reality or robotic machines.
A journal (Internet of Things Architectures: A Comparative Study) discusses different layers of IoT architecture [8]. Here is a proposal for 7 layer model of IoT. Big companies like Intel, Microsoft, Cisco, Google, Ericsson and Amazon have different views on IoT architecture. There were mainly two approaches such as the model of Analysis and Computer Architecture and the other was the comparative statement of the seven layer model. This journal was mainly concerned with the speed of IoT data transactions.
Education today is not limited to text and images but more than that most textbooks in the modern world are linked to web based sites that combine many additional materials that support education such as video evaluation animations and other materials to help students understand new things better and will help and greatly interact with their classmates
Regarding the Sustainable Education Systems in pandemic or in an unstable situation a research article [9] explores the role of Artificial Intelligence (AI) and the Internet of Things (IoT) in forming sustainable educational systems to boost student learning and academic performance during pandemic situations like COVID-19. The authors highlight the transformative potential of these technologies in providing interactive, efficient, and engagement of learning environments. Chatbots, Intelligent Tutoring Systems (ITSs), Automated Grading, Virtual and Remote Learning using AI Applications. Monitoring process, Interactive Learning Tools and Cooperation using IoT Applications.
For the new generation teaching education is not limited to books and lecture notes. IoT has opened the door for technological innovations to use different sources of teaching and learning. We can use applications like YouTube, Twitter, Facebook through AI based technology to provide more advanced learning.

3. Classification of education System:

Education systems can be classified into traditional & IoT-based smart education. The traditional education includes physical classrooms, face-to-face teaching, and static learning methods. IoT-based smart education integrates various connected devices and offering interactive, personalized learning, real-time feedback, and data-driven intelligences. The latter promotes flexibility and develops engagement, adapting to the modern educational needs and the technological advancements.

3.1. Traditional Education

We do not yet have any definite definition of smart learning. All the famous academics are giving different types on this subject. We can review some literature, According to Mr. Hwang, Scott and Benlamri, smart learning is context-aware ubiquitous learning [10]. And Mr. Gwak suggested that, firstly, it exposes the student and the content of the study and then the device, and secondly, it is effective, intelligent, tailor learning based on IT infrastructure.
A study outcomes the application of deep reinforcement learning for analyzing physical education, focusing on the role of IoT-enabled wearable devices in monitoring physical activities. A comprehensive framework was created and examined for students with different functional and physical capacities. The study's key contribution is twofold [11]:

1. Monitoring various physical activities such as walking, jogging, and sitting using IoT wearable devices for both physically active students and those who are practicing regularly.
2. Addressing challenges in providing IoT devices for effective activity monitoring, with a performance-oriented solution called IoT-PAMD.

The approach highlights the integration of IoT and wearable technology to enhance physical activity analysis and performance monitoring.

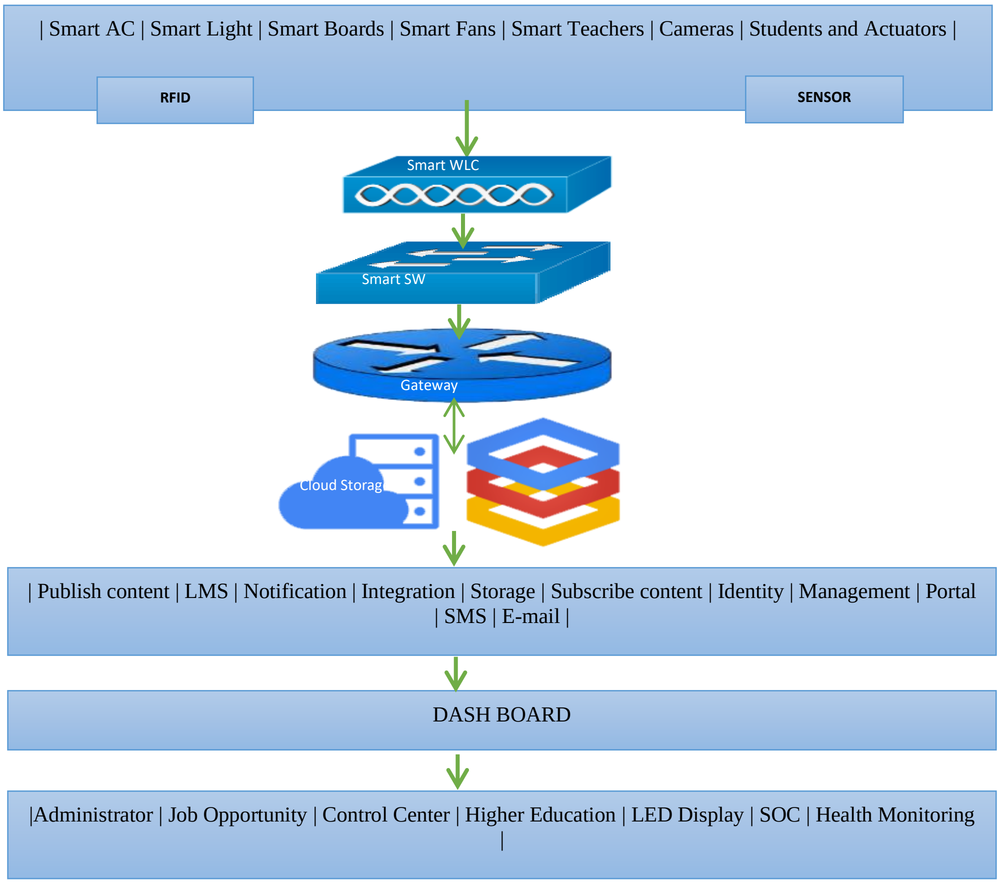

Fig.1. A traditional scenario of smart education

3.2. IoT based Smart Education system

The development of IoT in the education system has gone one step further due to the fact that it runs on very low power, small in size and low cost. Periodically IoT is gradually getting better and better.

People have been relying on the world-wide-web (www) for information collection for the first time. Through the evolution of four basic technologies, IoT technology is bringing a touch of modernity to the education system at the doorsteps of the world today.

- Internet broadband
- Mobile communications
- Social communication systems
- Cloud and computer systems

Mr. Kevin Aston first introduced IoT to the world in 1999, through his radio frequency identification (RFID) project. Since then, IoT has been moving forward with the message of victory in the realm of information technology **[12].**

In one study, Gartner, inc (2016) showed that by 2020, 20.4 billion IoT devices will be able to communicate with each other. This means that we will soon see the triumph of IoT all around us **[12].** This arrangement will help take education a long way. Multimedia projectors, smart boards and content management are having a profound impact on our education system.

4. Smart Education Architecture Analysis

Based on the information and communication technology presently learner-centered and effective learning is the backbone of modern educational technology. In this environment, the system can perceive the scenes of learning activities, and identify students' characteristics and select appropriate teaching resources for them automatically. As such, the teaching system of smart learning environment can record the learning process accurately and finish the learning evaluation in time. The teaching in the smart learning environment is carried out with the smart mobile devices as the electronic learning material. This learning material not only has all functions of paper textbooks, but also has multimedia and is individualized, which can link related knowledge points, analyze learners' learning results intelligently and show the results graphically, so as to provide some guidance for learners. The smart learning and the digital learning environment are in the context of many differences such as the learning resource & tool, teaching and learning methods, social community, etc. Excessively the multimedia facilities were required in a digital learning environment in the past. However for smart learning environment those required resources can be provided. So, now let's see the advantages of smart learning environment **[7]**.

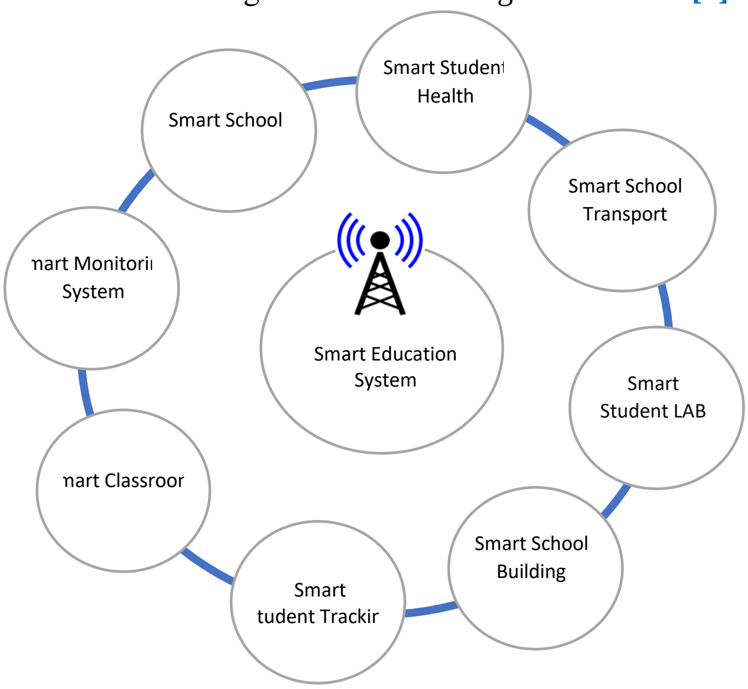

Fig.2. Component of IoT in

4.1. Limitation and Challenges

There are a number of issues and challenges for utilizing ICT technology in an e-Learning environment.

- Integration of artificial intelligent (AI) with Deep Learning
- Enhance IoT services by reducing a lot of network traffic

The integration of Artificial Intelligence **(AI)** with **Deep Learning** to enhance **IoT** (Internet of Things) **services** faces several challenges, particularly when **reduce network traffic** while maintaining efficiency, accuracy, and scalability [13]. Below is a breakdown of the challenges and solutions:

4.1.1 Network Congestion Due to Large Data Volumes

- **Challenge**: IoT devices generate massive volumes of data that must be processed and transferred to central servers or the cloud. Deep learning algorithms require significant assessment power and bandwidth to process this data.
- **Impact**: High network traffic, latency, and potential bottlenecks.

Solution:

- **Edge AI**: Deploy AI and deep learning models on IoT edge devices (Edge Computing). Edge devices process local data; and minimize the volume of data transmitted to the cloud.
- **Model Compression**: Use lightweight deep learning models, such as **MobileNet,** or techniques like **quantization**, **pruning**, and **knowledge distillation** to reduce the computational load.

4.1.2. Resource Constraints on Edge Devices

- **Challenge**: Sometimes IoT devices have limited computational power, memory, and battery life. Deep learning models on such devices can be highly inefficient.
- **Impact**: Device performance degradation and reduced battery life.

Solution:

- **Hardware Optimization**: Use improved hardware like **TPUs** (Tensor Processing Units), **AI chips,** or embedded GPUs to run deep learning models competently.
- **Federated Learning**: A decentralized AI approach where devices collaboratively train models without sending raw data to the cloud. Only the model updates that are shared reduce resource consumption.

4.1.3. Latency and Real-Time Processing

- **Challenge**: Many IoT applications, like autonomous healthcare monitoring, or industrial automation, require real-time decision-making with minimal latency.
- **Impact**: Delays in processing and transferring data may lead to critical failures.

Solution:

- **Real-Time Data Processing**: Use **on-device inference** for real-time decisions using deep learning models. Combine edge computing with **5G** for ultra-low latency communication.
- **Adaptive AI**: Implement dynamic models that process only essential data subsets, avoiding redundant computation.

4.1.4. Data Privacy and Security Risks

- **Challenge**: Transferring large volumes of sensitive IoT data to centralized servers or clouds raises privacy and security concerns.
- **Impact**: Exposure to cyberattacks and non-compliance with privacy regulations.

Solution:

- **Edge AI for Privacy**: By processing data locally, AI models can enhance privacy, so that raw data never leaves the device.
- **Homomorphic Encryption**: Ensure data is encrypted even during processing for secure deep learning methods.

4.1.5. Data Quality and Inconsistency

- **Challenge**: IoT devices may generate noisy, redundant, or incomplete data, which can negatively impact the accuracy of deep learning models.

- **Impact**: May reduced performance and increased processing overhead.

Solution:

- **AI-Driven Data Filtering**: Use **preprocessing algorithms** to clean and filter data locally on IoT devices before sending it to the cloud.
- **Data Fusion**: Combine inputs from multiple IoT devices to generate steady and reliable data for deep learning models.

4.1.6. Scalability Issues

- **Challenge**: Scaling IoT services while integrating AI and deep learning can be complex due to the growing number of devices and increasing data.
- **Impact**: Increased network traffic, higher costs, and challenges in managing distributed systems.

Solution:

- **Hierarchical IoT Networks**: Implement a multi-tier system where local edge devices handle initial processing and only aggregate results that are sent to higher levels (regional or central servers).
- **Decentralized AI**: Adopt distributed deep learning architectures to balance workloads across edge and cloud computing.

4.1.7. Energy Efficiency

- **Challenge**: Deep learning models are computationally intensive, consuming significant energy, which is a major limitation for battery-powered IoT devices.
- **Impact**: Limited device lifespan and frequent battery replacements.

Solution:

- **Low-Power AI Models**: Optimize deep learning models may reduce energy consumption. Lightweight frameworks like **TinyML** allow deep learning on ultra-low-power devices.
- **Sleep Mode Operations**: Develop AI models that can selectively activate IoT devices only when necessary to preserve energy.

The key to addressing these challenges lies in the integration of **AI, Edge,** lightweight **deep learning models**, and **distributed processing** techniques. By enabling local computation on edge devices and optimizing network communication, IoT systems can significantly reduce network traffic, enhance scalability, and improve performance. Technologies like **TinyML**, **5G,** and **Federated Learning** play a critical role in advancing these solutions.

4.2 The proposed 3D model emerged from real video

IoT Camera for Advanced Monitoring and Educational Support in Medical Hospitals

The proposed IoT camera may designed to monitor and analyze a wide range of activities in medical hospitals. It provides accurate suggestions and instructions, similar to those offered by a professional doctor. Additionally, the camera records activities and converts them into interactive 3D videos. These videos can serve multiple purposes, such as assisting other patients along with voice instruction or being used as educational material for students in physical education and related fields.

The IoT camera's observation capabilities extend across various domains like Dance and Movement Analysis, Ball Handling Techniques, Athletic Performance, Games and Recreational Activities, Components of Physical and Support Education, Gymnastics, Outdoor Education to sports Skill Development.

By leveraging this technology, the system ensures comprehensive monitoring and instructional support. It may not only enhances patient care but also contributes expressively to the training and skill development of students and professionals in physical education and healthcare.

Creating an IoT camera system that captures all real video and converts it into a 3D model involves several stages. Below is a high-level outline of the process, including necessary technologies and sample code snippets for implementation [14]:

4.2.1. Key Components

IoT Camera: Raspberry Pi with a camera module or an IP camera for real-time video capture.

Edge Device: Process captured video frames using computer vision and send data to the cloud.

3D Model Processing: Use photogrammetry techniques or depth estimation to create 3D models from video frames.

Visualization: Display the generated 3D models on a user interface.

4.2.2. Technologies Needed

Programming Language: Python, C++, or JavaScript (depending on the edge device and software requirements).

Libraries:

OpenCV: For video frame processing.

Mediapipe/DepthAI: For depth estimation.

Open3D/PyTorch3D: For 3D model generation.

Cloud Services: AWS/GCP for 3D model rendering and storage.

IoT Framework: MQTT or HTTP for communication between the camera and cloud services.

4.2.3. Flowchart of the Model:

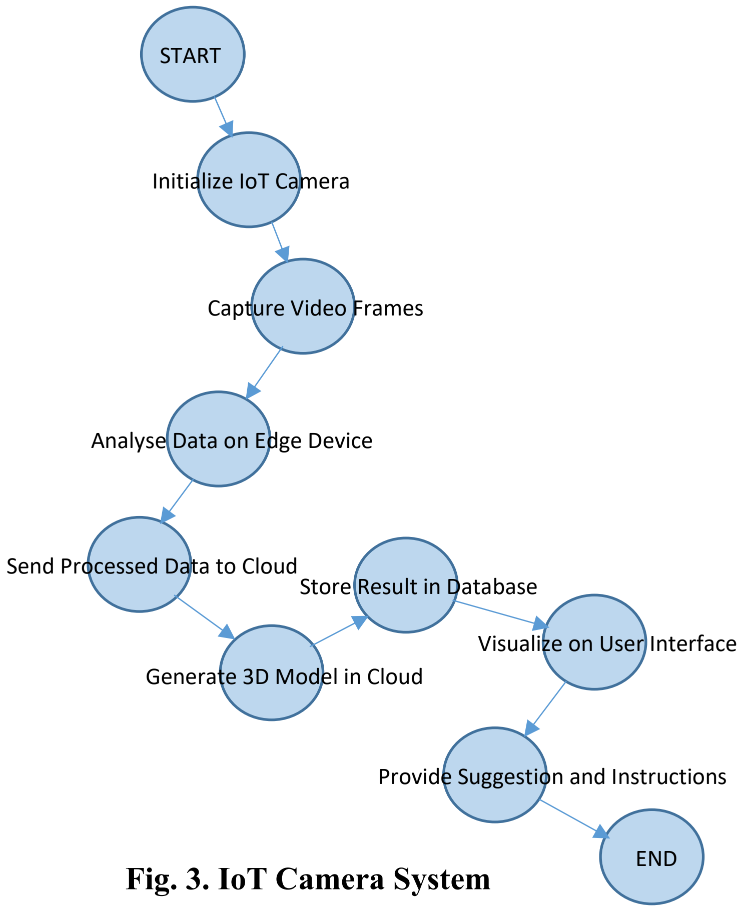

Fig. 3. IoT Camera System

The process of **3D** modeling in the context of the IoT camera system involves capturing video frames and converting them into a 3D representation using techniques like depth estimation, photogrammetry, or volumetric reconstruction. Working process stated here step-by-step:

4.2.3.1.Video Capture

- The IoT camera will continuously captures video frames of the subject like patient movements, physical activities, etc.
- High-resolution frames will store locally or stream to an edge device for processing.

4.2.3.2.Key Frame Selection

- Not all frames are used. A selection algorithm identifies keyframes that capture unique perspectives of the object or subject.
- These frames are analyzed for significant details (angles, motion).

4.2.3.3.Feature Detection

- **Computer Vision** techniques identify distinct points (features) in the key frames:
  - Corners, edges, or unique patterns.
  - Algorithms like **SIFT (**Scale Invariant Feature Transform**)** or **ORB (**Oriented FAST and Rotated BRIEF**)** are used.

4.2.3.4.Depth Estimation

- **Stereo Vision**: If the camera setup includes multiple cameras, depth is calculated using the disparity between images from different camera angles.
- **Monocular Depth Estimation**: For single-camera systems, depth estimation models (deep learning frameworks like MiDaS) predict depth maps from 2D frames.

4.2.3.5.Photogrammetry

- Photogrammetry is used to reconstruct the 3D shape of the object from multiple 2D frames:
- Following features the frames are aligns.
- Calculates 3D positions for the points in space (point cloud).
- Tools like OpenCV, Meshroom, or commercial software like Agisoft Metashape to automate this process.

4.2.3.6.Point Cloud Generation

- The identified 3D points are combined into a point cloud.
- A point cloud represents the surface geometry of the observed object.

4.2.3.7.Mesh Generation

- The point cloud is converted into a mesh using algorithms like Poisson of Surface Reconstruction or Delaunay Triangulation**.**
- The mesh creates a continuous surface by connecting the points with triangles.

4.2.3.8.Texturing

- The textures and colors applied to the mesh for realism.
- Texture mapping the takes to pixel data from the video frames and projects it onto the 3D mesh.

4.2.3.9.3D Model Optimization

- The model optimized to reduce the file size while maintaining details.
- This step includes simplifying the mesh and compressing textures for quick rendering.

4.2.3.10. Visualization

- The 3D model visualized using below tools.

- **WebGL** for web-based platforms.
- **Unity** or **Unreal Engine** for interactive applications.
- Custom-built visualization software.

4.2.3.11. Tools and Frameworks

- **OpenCV:** Feature detection, point cloud generation.

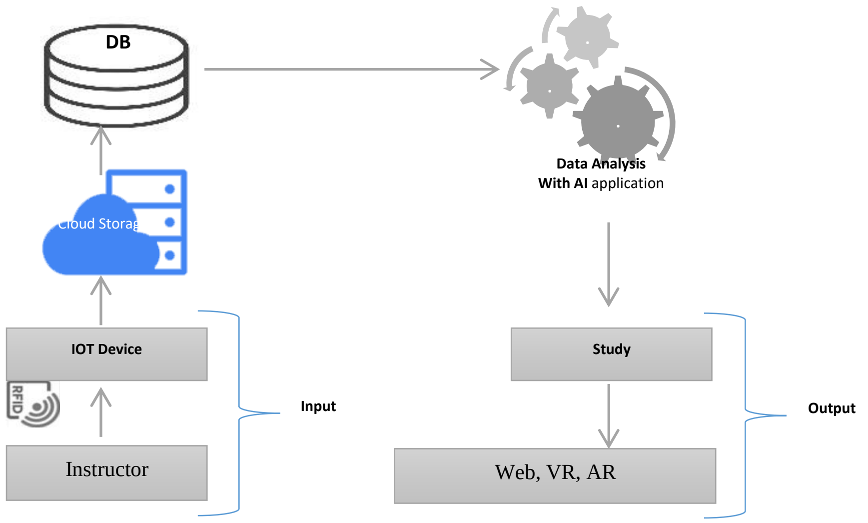

Fig.5. AI based system architecture with IoT

- **PCL** (Point Cloud Library)**:** For handling the 3D point clouds.
- **Blender:** For advanced 3D modeling and visualization object.
- **TensorFlow or PyTorch:** For depth estimation along with deep learning.
- **Meshroom:** Free photogrammetry software for creating the 3D models**.**

4.2.3.12. Applications

- **In Medical use**: Create 3D anatomical representations for educational purposes.
- **In the Activity Analysis**: Visualize patient movements in 3D for training or monitoring.
- **In Interactive Content**: Render the 3D models for student learning or skill development.

4.3. Integration of Artificial intelligence (AI) with Deep Data mining technology.

Our current education system is based on instruction. That is, our education system is trapped within four walls. We are all made through this method. There is no scope for collaboration, personalized learning and differentiated learning. It's a very old method [15]. With this method it will not be possible to create skilled manpower for the Fourth Industrial Revolution. So have to go for any alternative method that already tested [16]. And that method can be smart education. This will require a smart classroom.

One study found that if 30 students were taught in a classroom by a teacher, the quality of their education was the same. He has learned a little more if he is taught in a mastering way. Then the results are better if the teaching is done in one to one or tutoring method. If we want to make our classrooms smart, we have to do it through technology. Then we will be able to teach students through one-to-one, mastering and tutorial learning technology.

Now, if basic education has to be made smart, then science, technology, engineering, arts and mathematics education can be given using technology. This could be through robots, artificial intelligence or artificial intelligence (AI) or programming.

The proposed application can be developed through Java programming and used "Hadoop" as an analysis engine **[12]**. This architecture has three modules as shown in Figure-3.

1. Sensors devices and data Concentration centre.
2. Data analysis
3. Data visualization.

4.4. Traditional AI based System Architectural workflow:

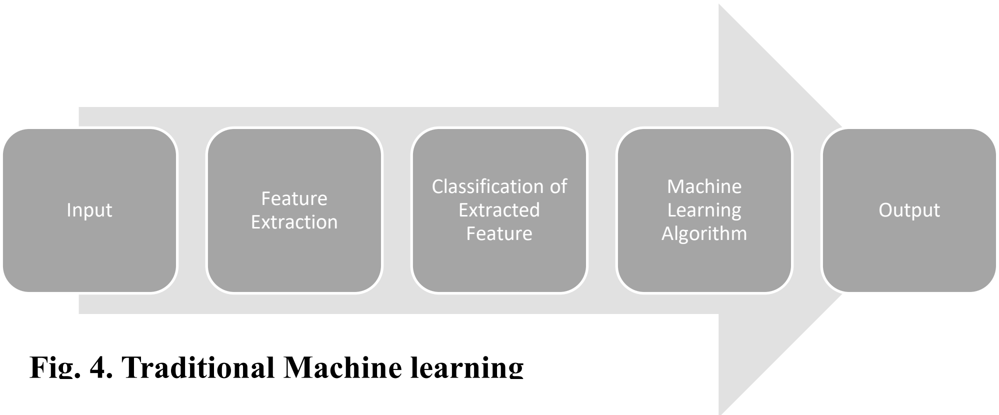

Fig. 4. Traditional Machine learning

Traditional AI based System Architectural workflow:

After first inputting data for machine learning, various features of data are extracted **[17]**. Then various classifications of extracted features are completed such as Logistic Regression, Naive Bayes Classifier, Nearest Neighbour, Support Vector Machines, Decision Trees, Boosted Trees, Random Forest and Neural Networks. Finally, machine-learning algorithms Such as supervised learning, Unsupervised Learning, Semi-supervised Learning, Reinforcement Learning, are applied. In this case the processing time is more for two steps which showed in Fig.4.

4.5. Steps in traditional AI based IoT data processing

Data Collection and transmission with sensors:

Different religious sensors will be included in different educational institutions for different types of data collection and this collected data will be sent to a cloud-based centralized database.

Data Center (Deliberation)

The collected data will be processed with Artificial Intelligence based algorithms. This stage will be completed before the data is sent to the cloud. The management of all smart objects such as IoT will be effective. Education composition abstraction will be completed and security will be ensured at this stage.

Analytics and Visualization in Cloud Processing

Data analysis will be done at this stage to visualize and make it usable. Data will be classified following this stage. Neural network technology will solve this stage completely.

5. The potential of using augmented reality (AR) in conjunction with IoT and deep learning:

Combining Augmented Reality (AR) with IoT and Deep Learning can significantly enhance learning **[18]**. Below is an overview of how these technologies might work together to improve education and training **[19]**:

- **AR** delivers engaging visuals and simulations tied to physical environments.

- **IoT** provides real-time contextual triggers like location, object interactions.
- **Deep Learning** personalizes content, enables object recognition, and supports conversational AI.

Applications include STEM education, cultural exploration, skills training, and language learning. Challenges include hardware costs, data privacy, and scalability. Emerging technologies like 5G and edge computing will further enhance these capabilities, making education dynamic and impactful.

Challenges [20]	**Solutions**
High cost of AR and IoT infrastructure	Use affordable devices like smartphones and IoT kits
Complex integration of systems	Develop standardized platforms with APIs.
Privacy and security of IoT data	Implement strong encryption and data protection protocols.
Content creation and scalability	Use AI to generate AR content dynamically

6. **Monitor cognitive load and emotional states of wearable IoT devices to optimize the pacing and difficulty of online learning content in real-time.**

Wearable IoT devices monitor **cognitive load** via EEG, HRV, eye tracking, and **emotional states** like skin conductance & facial cues to optimize online learning in real time. They adjust pacing, difficulty and provide feedback based on signals like stress or engagement. For example, detecting frustration can trigger simpler tasks or motivational prompts. Challenges include data privacy, sensor accuracy, and algorithm reliability, but advancements in AI and edge computing promise improved personalization and engagement in learning **[21]**.

7. **Integration of smart home devices with online learning platforms to create adaptive learning environments that respond to factors like time of day, noise levels, and ambient lighting.**

Integrating smart home devices with online learning platforms creates adaptive environments by tailoring conditions like lighting, noise levels, and temperature to enhance focus and productivity. Key features include **[22]**:

- **Time Optimization**: Smart assistants schedule study sessions based on energy patterns.
- **Noise Control**: Sensors detect disturbances and recommend headphones or pause sessions.
- **Lighting Adjustments**: Smart lights adapt brightness and tone for reading or problem-solving.
- **Temperature Control**: Thermostats ensure a comfortable learning space.
- **Voice Commands**: Hands-free navigation of learning platforms via smart speakers.
- **Wellness Insights**: Wearables monitor stress or fatigue, adjusting intensity or recommending breaks.

8. **A system may uses deep learning to analyze patterns in learners' daily routines and automatically schedules short, targeted learning sessions during optimal times.**

To build a system that uses deep learning to schedule optimal learning sessions:

- **Data Collection**: Gather daily routines, activity logs, sleep patterns, and user preferences from devices, calendars, and wearables.
- **Preprocessing**: Clean data, extract features like strength activity, focus on times and normalize time-series data.

- **Model**: Use RNN/LSTM or Transformer models to analyze patterns and predict optimal learning times.
- **Scheduling**: Combine model predictions with a scheduling algorithm to recommend short, targeted sessions.
- **Feedback Loop**: Integrate user feedback via reinforcement learning to refine timing and session effectiveness.
- **Deployment**: Build a mobile/web app for interaction and deploy the backend on cloud platforms like AWS or Firebase.

Key tools: TensorFlow/PyTorch for deep learning, Firebase for storage, and APIs like Google Calendar for integration.

9. Potentiality of using IoT-enabled public spaces as unprepared learning stations that deliver personalized educational content.

IoT-enabled public spaces, like smart bus stops and interactive billboards, can serve as impromptu learning stations by providing personalized, interactive educational content. Using IoT devices, AI, and connectivity, they can deliver quick lessons, tutorials, or gamified learning experiences tailored to users' interests [23].

Benefits:

- Accessible education during downtime.
- Enhanced engagement through interactive features.
- Integration with smart city initiatives.

Challenges:

- Data privacy concerns.
- High infrastructure costs.
- Maintaining content relevance and engagement.

Implementation:

Pilot programs in urban areas, partnerships with educational and tech organizations and AI-driven content management can drive this concept forward, making learning accessible and engaging in everyday public spaces.

10. Federated learning techniques and maintain privacy while allowing deep learning models to learn from distributed IoT data across multiple learners and environments.

Federated Learning (FL) is an innovative technique that enables deep learning models to learn from distributed data across multiple IoT devices while maintaining privacy. In this framework, the data remains localized on the devices, and only model updates of gradients or weights are shared with a central server for aggregation. This ensures data privacy and minimizes security risks [24].

Key Features in IoT Environments:

- **Data Privacy**: Sensitive data, such as health metrics from wearables or environmental sensors, never leaves the device.
- **Reduced Bandwidth**: Transmitting model updates requires less bandwidth compared to raw data transfer.
- **Personalized Models**: Devices can maintain a global model while adapting it locally for specific environments or user behaviors.

Challenges:
- **Heterogeneity:** IoT devices vary in computational power, connectivity, and data distribution.
- **Communication Efficiency:** Frequent model updates can still be bandwidth-intensive; techniques like compression and sparse updates help mitigate this.
- **Security:** FL is susceptible to model poisoning or adversarial attacks.

Applications:
- **Smart Healthcare:** Learning from distributed health data without compromising patient privacy.
- **Smart Cities:** Aggregating data from sensors to improve urban planning while ensuring citizen data remains local.
- **Predictive Maintenance:** Leveraging data from industrial IoT devices for fault prediction without exposing proprietary information.

Federated learning is a promising approach for privacy-preserving AI in IoT, balancing efficiency, personalization, and security.

Federated learning (FL) is a powerful approach to train deep learning models across distributed devices, such as IoT networks, while preserving data privacy. Here's an in-depth exploration of how FL can be applied to IoT environments:

11. Framework for adaptive, collaborative learning experiences that use IoT and deep learning to match learners with nearby peers for study sessions or discussions.

A. **Objectives**:
- Personalize learning with adaptive AI.
- Foster peer-to-peer in-person collaboration.
- Leverage IoT for location and environmental awareness.

B. **Core Components**:
- **Learner Profiling**: Collect data on goals, skills, and availability; use AI to identify strengths and learning styles.
- **IoT Ecosystem**: Track locations and detect study-friendly environments via smart devices.
- **Matching Algorithm**: Deep learning for dynamic pairing or group formation based on proximity and complementary skills.
- **Scheduling**: Sync with calendars and suggest optimal times and venues.

C. **Workflow**:
- Collect data → Analyze profiles → Match learners → Schedule sessions → Monitor attendance → Gather feedback.

D. **Technologies**:
- IoT sensors/devices, deep learning frameworks (TensorFlow, PyTorch), Firebase/AWS IoT for backend, React Native for UI.

E. **Evaluation**:
- Measure engagement, skill improvement, and matching efficiency.

F. **Scalability**:
- Expand IoT coverage, support cross-institution connections, and allow user customization for preferences.

This streamlined system integrates IoT and AI to create adaptive, collaborative learning experiences.

12. Deep learning to analyze data from IoT-enabled textbooks and learning materials to provide real-time feedback on reading comprehension and engagement.

Deep learning can analyze data from IoT-enabled textbooks to provide real-time feedback on reading comprehension and engagement by leveraging:

A. **Data Collection**: IoT sensors gather eye-tracking, page interaction, biometric, and voice data.
B. **Preprocessing**: Normalize and segment data into actionable insights.
C. **Deep Learning Models**:
- **NLP:** Assess comprehension using models like GPT or BERT.
- **CNNs:** Analyze eye-tracking heatmaps and facial expressions for engagement.
- **RNNs/Transformers:** Detect trends in reading behavior and focus areas.
- **Multimodal Learning:** Combine textual, visual, and biometric data for a holistic view.

D. **Feedback Mechanisms**:
- Real-time prompts, adaptive content recommendations, and engagement alerts.

E. **Applications**: Personalized learning, instructor dashboards, gamification, and accessibility improvements.

This approach enhances learning experiences by making educational tools smarter and more tailored to individual needs.

13. Potentiality of IoT sensors and deep learning to create dynamic, adaptive assessments that evolve based on the learner's performance and environmental factors.

Using IoT sensors and deep learning, dynamic assessments can evolve in real time based on a learner's performance and environmental factors. IoT devices collect data on engagement, stress, and surroundings, while deep learning algorithms analyze this data to adjust question difficulty, pacing, and feedback. This approach personalizes learning pathways, enhances engagement, and supports diverse use cases like education, corporate training, and special education. Challenges include privacy, integration, and cost, but advancements in edge computing and VR integration could make adaptive assessments transformative for personalized learning.

14. A system that may use deep learning to analyze IoT data from multiple learners to identify and address gaps in understanding across entire communities or demographics.

The system will utilize IoT devices for data collection, deep learning models for processing, and analytics to provide actionable insights. The objective is to identify patterns of misunderstanding or knowledge gaps across communities or demographics to improve learning outcomes.

System Components:

14.1. IoT Data Collection Layer

- **Devices**: Sensors in wearables, smart classrooms, mobile devices, or AR/VR systems that monitor learner activities such as:
  - Engagement levels via eye-tracking, gestures
  - Test/Quiz answers and response times
  - Physical activity during learning sessions
  - Speech and voice inputs like asking questions

- **Data Types**:
  - **Structured**: Logs of correct/incorrect answers, response times, attendance data.
  - **Unstructured**: Audio, video, and behavior data.

14.2. Data Processing and Storage

- **IoT Gateway:** Aggregates data from IoT devices in real-time and filters it for relevance.
- **Edge Computing:** Processes some data locally to reduce latency and bandwidth usage.
- **Cloud Storage:** Centralized repository for large-scale historical data.

14.3 Deep Learning Model Architecture

The system will employ various deep-learning models to analyze different data types [25]:

Natural Language Processing (NLP)

- **Task:** Analyze text-based inputs such as responses, queries, or answers.
- **Model:** BERT, GPT-4 fine-tuned for educational content analysis.

Computer Vision

- **Task:** Analyze video for attention detection, facial expressions, and physical engagement.
- **Model:** CNNs (ResNet or EfficientNet) combined with Vision Transformers (ViT).

Time-Series Analysis

- **Task:** Process learner response times and trends.
- **Model:** LSTMs or GRUs for sequential analysis.

Multimodal Learning

- Combines inputs from different sources (audio, video, text, and behavioral data) to identify broader trends.
- **Model:** Fusion-based models like MMTM (Multimodal Transfer Module).

14.4. Gap Analysis Engine

Feature Engineering: Extract learning features such as:

- Mistake frequency by topic.
- Inattention detection during specific activities.
- Inconsistent response times.

Demographic Aggregation:

Group data by location, age, community, gender, or socioeconomic background to identify patterns.

Deep Learning Insights:

- Highlight **misunderstood topics** across a community.
- Predict areas where learners are likely to struggle.
- Suggest solutions based on historical successful interventions.

14.5. Dashboard and Visualization

Provide **stakeholders (teachers, institutions, policymakers)** with intuitive dashboards:

- Knowledge gap heatmaps.
- Engagement and performance metrics across demographics.
- Trend analyses for improving curriculum delivery.
- Recommendations for targeted interventions.

14.2. Workflow

a) IoT devices collect and send learner activity data.
b) The IoT gateway processes the data and stores it in the cloud.
c) Deep learning models analyze the data to:

- Identify trends in learner behavior and performance.
- Correlate results across demographics to detect community-level knowledge gaps.

d) The system generates actionable insights and visualizes them in an easy-to-interpret dashboard.

14.3. Technical Stack

- **Frameworks**: TensorFlow, PyTorch, OpenCV, HuggingFace Transformers.
- **Cloud Services**: AWS IoT, Google Cloud IoT Core, Azure Machine Learning.
- **Databases**: MongoDB, PostgreSQL, or cloud-based solutions like AWS DynamoDB.
- **Visualization**: Power BI, Tableau, or custom React dashboards.
- **Deployment**: Docker containers with Kubernetes for scaling.

15. DESU in AI based System Architectural workflow:

The IoT device will collect the data from different levels of the educational institution and store it in the database. This data is then converted into standard data which will be automatically refined through various programming platform Data Encryption and Standardization Unit (DESU) and machine learning software. The process is as follows.

- <u>Data Source identification and Authentication:</u> Since IoT devices have a lot of sensors in this case, it maintains certain security through DESU.
- <u>Data size and type identification:</u> Collects through IoT sensor determining DSE and data identification and data size.
- <u>Choosing data Standards:</u> Since not all the data collected is of the same nature, DESU will decide how and by what standard the data can be collected.
- <u>Data Cleaning:</u> Since there will be a lot of noise in the data and a lot of duplicate data may be present, DESU will decide how to clean the data and clean it through specific programming.
- <u>Data Normalization:</u> At this stage there will be data normalization through data restructuring which will be suitable for use in the next stage.

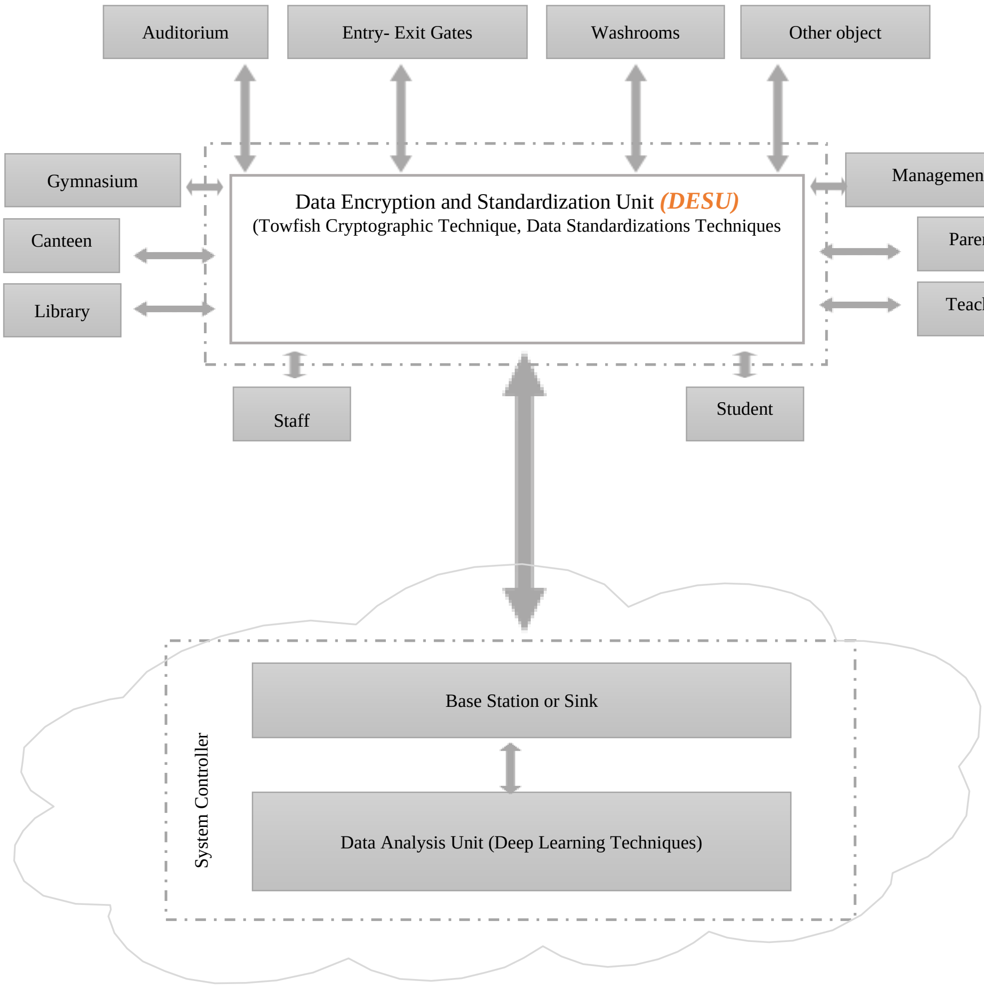

Fig.6. Architecture of Artificial Intelligence IOT Machine learning Approach

The Artificial Intelligence System displayed an excellent example of Deep Learning **[26]**. In this process data features extraction and classification are done simultaneously making the process smarter in less time.

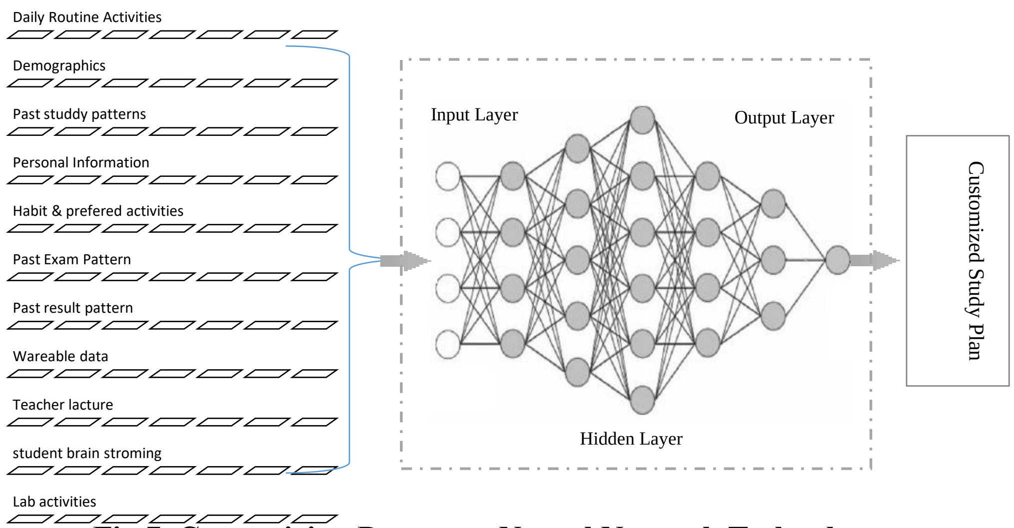

Fig.7. Customizing Data over Neural Network Technology

After completing the above steps, the data collected from the sensor is converted to a standard value and then the formatted data Transfer to the encryption unit which protects the data integrity.
After the data is encrypted, it is sent to the base station where the data can be stored and works in the cloud following the correct instructions of the system controller.
The Data Analytics Unit then makes the data readable with the help of Deep Learning Technology and Artificial Intelligence Algorithm.
Thus the data transfer from one unit to another unit in less time within the security zone of SDN (Software Defined Network).
This SDN technology transmits the data dynamically according to the shortest path, which increases the North-South transaction of the data but decreases the East-West transaction to a great extent. As a result, the service can run in much less time. The SDN controller can control data traffic [27].
Data Processing with AINN (Artificial Intelligence Neural Network) Technology:

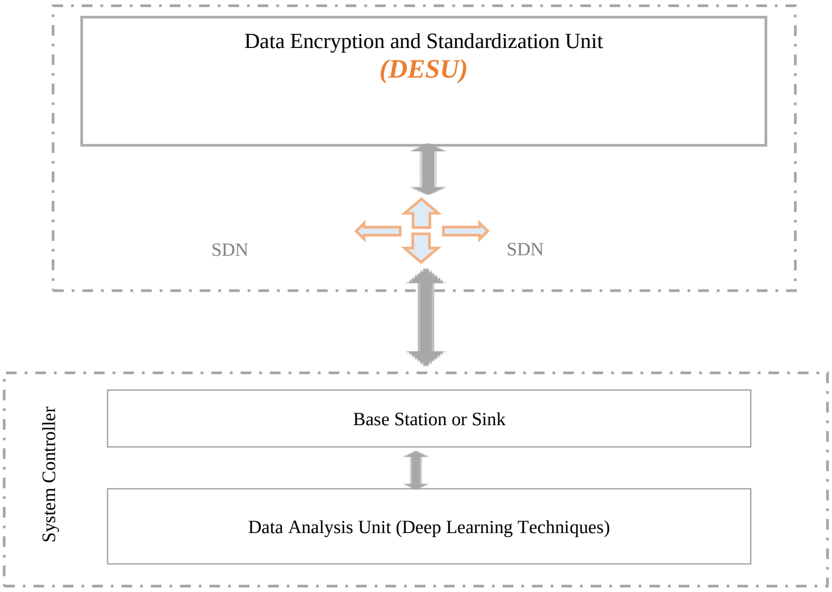

Fig.8. Architecture of Artificial Intelligence with SDN Approach

Data can be transformed by following the processes

- *Analytics of Content:* Deep Learning Technology of AI reconstructs the collected data through analysis and converts it into usable and optimistic data.
- *Development of adaptive learning strategies:* It is improved by continuously collecting data from students-teachers and converting educational data.
- *Gap analysis of teaching and learning:* collecting previous and subsequent data from student and teacher, this process can gap analyze by analyzing its character.
- *Customize the data of teaching and learning:* Deep learning technology can customize learning data through different correlations using different algorithms.

16. Artificial intelligence in the development of smart education (Pros & Cons)

While AI has immense potential to revolutionize education by improving accessibility, efficiency, and engagement, it also presents challenges like high costs, ethical issues, and reduced human interaction. A balanced approach that integrates AI with human teaching can maximize benefits while mitigating drawbacks [28].

- Lerner can ask historical and research questions on any subject online or through virtual reality. Artificial intelligence can be a virtual teaching system through data mining processes.
- This technology is not far away now it is in our hands which are in practical condition when this technology will be fully improved then we will get digital intelligent teacher.
- Artificial Intelligent Teaching system will deliver by understanding the condition of the students. By analyzing Lerner's intelligence, Artificial Intelligence will make suggestions and help on its own.
- To help learners find and solve problem
- Through intelligent changes in teaching data, teachers and learners will be able to do research more efficiently.
- With Artificial Intelligence, software can easily set up student grading systems.
- Adaptation of this system will be able to solve the problem in a very short time.
- Artificial Intelligence understands whether learners gave wrong or correct answers by Pattern Analyzing.

17. Summery analysis compares table

Architecture	Data Analysis	Education Material	Processing Speed	Storage Medium
Fig-1	No	Raw data	Reduce east-west traffic	Cloud
Fig-2	No	No	Good	No storage
Fig-3	Yes	Processed by AI	Better	Cloud
Fig-5	More than Fig-3	Processed by AI with	Better	Cloud / Edge
Fig-6	Deep learning	Secured	Best	Cloud / Edge
Fig-7	Deep learning	Secured and speedy	Best than Fig.6	Cloud / Edge
Fig-8	Deep learning	Secured	Best than Fig.7	Cloud / Edge

18. Advantages of the presented approach

- Established Security and authentication in education system and material of education;
- Reduced of IoT based component’s power consumptions
- Systematic attendance system of Student, teachers and staff
- Smart teaching and learning activities in an intelligent way
- Student’s Health care and hygiene
- Automated and smart library management system

19. Conclusion

In conclusion, this study demonstrates the potential of integrating IoT sensors and deep learning techniques to create personalized, context-aware educational experiences in smart cities, highlighting significant advancements in the field of educational technology.

Our main goal is IoT based education system architecture development. We know that IoT devices can collect data from all educational institutions and send it to the cloud.
By collecting data through data mining from different educational institutions of the world, we can classify the data through Artificial Intelligence technology and use this data through any subsequent educational delivery system where no teacher will be needed. This IoT based AI that means neural network technology could be the digital teachers of next generation.
Future research could explore the scalability of this approach across different educational settings and investigate the long-term impacts on student learning outcomes with value and engagement.
Authorship Contributions on Credit: The author, **Mohammad Amir Hossain**, conducted the literature review, hypothesized and designed the study, and developed the theoretical framework for integrating IoT sensors and deep learning in smart education. **Mr. Taqi & Mr. Raza** carried out data analysis, drafted the manuscript, **Mr. Al Mamun** created visualizations for the proposed architectures and models and **Mr. Jami Yaseer** played grate role on analysis, table creation and collaboration of project.
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Ethics Statement: Study did not involve any human or animal subjects, eliminating the need for ethical approval. All sources and references have been properly cited with academic integrity.
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