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# A DEEP LEARNING MODEL FOR EDUCATION ANALYTICS – A SHORT REVIEW

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**ABSTRACT**

Integrating deep learning with learning management systems can result in intelligent course material and high accuracy without any manual intervention. This paper reviews factors that influence deep learning in education, and hence this article aims to achieve deep learning on a large scale in the smart education system with a deep learning model to predict. The proposed model can reduce development and maintenance costs, reduce risks, and facilitate communication between stakeholders.

**Keywords**: Educational Technology, Machine Learning, Deep Learning, Smart Education, Smart Learning, Learning Analytics.

**HIGHLIGHTS:**

1. **The current review focus on deep learning as an important tool for Indian teachers.**

## INTRODUCTION

Decreasing technology costs and growing free online resources make educational technology within reach of Indian teachers and students. Predicting the dropouts, improving teacher-training quality and making personalized education a reality are challenges [1] in the present technology-based education system. Some of the challenges are listed below:

- Personal privacy: Parents or guardians are not comfortable sharing data on their children without a strong understanding of why it is needed.
- Educators must remain cognizant of bias: The teachers are biased. If the data is geared toward a specific demographic, then the output will be limited.
- Data storage becomes a significant concern for educational institutions increasingly collecting massive amounts of data to inform education.

These challenges make greater use of learning approaches in the education system. The educational technology needs to provide a clear and understandable value proposition to families and operate with complete transparency. It needs learning methods that can help overcome bias in the classroom - perhaps even more so than teachers can do themselves. An efficient learning approach is required to process a massive amount of educational data and predict the output.

In the education system, the stakeholders are students, teachers, staff members, educators, parents, recruiters, other educational institutions. The entities are libraries, entry-exit gates, canteens, auditoriums, laboratories, hostels, medical, classrooms and gymnasiums. The educational premises may be embedded with the Internet of Things (IoT) or sensor-enabled devices. These devices can sense, capture the data in the learning environment, and send it to further educational applications. The data produced by the IoT devices or sensors can be massive and unstructured. These vast data have to travel from source to destination and vice versa using a wired or wireless medium.

Educational institutions can use these data for processing for various purposes, including analytics and prediction. Recently Deep Learning (DL) techniques (Figure 1) have been used to perform better analytics and forecasts on a massive volume of data. DL leverages an artificial neural network (ANN) to build a model for predictions with speed, scale, and judgment that exceed human capabilities. DL methods are more effective than

Machine Learning (ML) approaches with the larger scale training set, smaller model, and more effective detections.

The objective is to introduce DL methods in the smart education and propose a model for the smart education system. The proposed DL model can predict better educational outcomes, improve teachers' training quality, and make personalized education a reality.

Smart education is an advanced learning method that has to be imbibed as a way of life in learning in developing countries. Thus, smart learning is an amalgamation of human intellect aided by tools and devices to bring precision education. Smart education consists of two important components.

1. Smart Learning Environment (SLE): The components of SLE are learner classification and intervention feedback. The objective is to understand the different learners with different types of information to classify the learner. SLEs can be considered context-aware computing systems. The recommendation system frequently assesses the learning's ability and employs it as the main factor for providing the appropriate response. In SLE, all dynamic changes are observed, interpreted, and responded appropriately.
2. Smart Learning Analytics (SLA). Both educational data mining (EDM) and learning analytics (LA) aims to improve educational experiences by helping stakeholders of educational institutions [2]. Making better decisions using learning data can boost the computing capacity, store and analyze massive data, and the availability of statistical, learning, and data-mining methods and techniques. SLA means discovering, analyzing, and making sense of student, instruction, and environmental data from multiple sources to identify learning traces to facilitate instructional support in authentic learning environments. Some SLA examples are procedure evaluation e-Learning e-Training tool, augmented reality testing (ART), CODEX, MI-DASH, SCRL and 2WRITE.

Smart Education Model (SEM): Smart education solution [3] is designed based on the technologies available to meet the requirements of teachers, students, parents, staff, etc. It is also designed to scale learning data (e-content) and business or educational functions. Smart education solution has an education cloud platform that includes smart campus, e-resources, intelligent devices, social communications, and system integration services. An intelligent education platform provides teaching, learning, resources, data analysis, and other services. It can assist teachers in teaching research and make a personalized learning plan for students. It can also help to communicate between home and higher education institutions and efficient management. Various sensors (e.g., temperature, humidity, heartbeat, and photo) can be used in a smart classroom.

Smart education is equipped with smart information, interactive boards, a learning environment, smart devices, LMS, apps, Data Centres, dashboards, communication & collaboration, etc. [4]. The students can connect to the LMS portal through their smart devices – smartphones, tablet, and desktop computers using wireless or mobile, near field communication, Bluetooth. The students can get the latest information about their studies, classes, contents, assignment, and examinations. All collected data in SLE are processed to Datacenters equipped with different servers, including portal, LMS, storage, analytical, blockchain, gateway servers, etc. All collected data can be processed, and results can be informed to the students through e-mail, SMS, social networks, etc. The educators or administrators can view these details through the facility of the dashboard. The proposed model allows collaboration among students, teachers, parents, administrators, and staff smartly. This model enables innovative approaches, methods, strategies, etc., to improve educational processes, useful for smart learning systems. Overall, this model enhances the environment and customizes the students' needs.

*Deep Learning in Smart Education*

The smart education system produces a large amount of data. Thus, DL methods are suitable for the smart education system. DL can automatically extract complex representations from data. DL methods can enable the deep linking of the SLE. The smart devices and sensors in an SLE can automatically interact to form an intelligent education. DL methods provide a computational architecture that combines several processing levels (layers) to learn data representations with several abstraction levels, as shown in Figure 2.

Academic analytics and data mining techniques have emerged in the wake of higher education's ability to capture an increasing volume of data [5]. The concept of data mining in higher education surged at the advent of the Internet. Academic analytics combines select educational institutional data, statistical analysis, and predictive modeling to create intelligence on teachers, students, and educators to change academic behavior. DL methods fine-tune insights about the data, learning, and behavioral patterns to improve the results' accuracy. It can create a learning analytics system for the students. DL methods can create content analytics to dynamically restructure and optimize the content modules as per the students' needs. With this, it is to track students' learning and suggest measures for further improvements. DL methods can devise novel and formative test formats and challenge them to develop new strategies for studying such startling structures. This approach enhances the students' thinking capabilities, cognitive ability, and retention, thus thriving in academics.

DL methods create a system for getting the teachers' customized lecture plans for students' particular groups or courses. They are also used to adopt the continuous inputs from the students and observations of the teachers. DL methods allow the teaching-learning gap analysis to improve the overall teaching-learning process. They can train the education system to process the inputs from the students and teachers and suggest customized teaching-learning methods applicable to different groups of students.

In the smart education model, the stakeholders and other entities within the educational system premises are embedded with sensors, actuators, and transponders using wearable and fixed devices. The stakeholders are students, teachers, staff, recruiters, parents, etc. The sensors in these entities can sense and capture the information about themselves and their environment and then send the data to the base station for further processing. These sensors produce a vast amount of data, traveling from source to destination and vice versa using a wired or wireless medium.

Figure 3 presents an overview of the architecture of the proposed approach. It uses deep neural network architecture loosely inspired by the structure of biological brains. A neural network's key benefit is the ability to create a flexible, bespoke model for an individual business, which is based on its fraud, which gives greater accuracy. It makes separate neural networks that focus on different aspects of the students: their behavior, the natural language associated with them, their activity, or any image data related to them. It combines the layers in these networks into a singular model. This final neural network is trained to learn which aspects of the individual learners are most important for analytics.

To optimize bandwidth and faster data transfer, educational institutions can incorporate the concept of software-defined networking (SDN). DL techniques have been used to perform better analysis and predictions using the data received from these sensors.

DL algorithms can learn from historical patterns and recognize them in future transactions. DL algorithms appear more effective than humans do when it comes to the speed of information processing. Some of the requirements to build a DL model to smart education analytics are listed below:

1. **Accuracy:** DL can often be more effective than humans at uncovering non-intuitive patterns or subtle trends, which might only be evident to a fraud analyst much later.
2. **Efficiency:** Machines can take routine tasks and manual analysis of dirty work, while specialists will only spend time making more high-level decisions.
3. **Scalability:** DL methods show a better performance along with the growth of the dataset to which they are fitted.
4. **Speed:** Interaction in e-Commerce applications is so dynamic that things can change significantly within a few hours or days. DL methods will come in handy to learn new patterns.

Smart education analytics using DL starts with gathering and segmenting the data. Then the DL model is fed with training sets to predict the probability of anomaly.

1. **Extract Data:** The data will be split into three different segments – training, testing, and cross-validation. The algorithm will be trained on a partial set of data and parameters tweaked on a testing set. The performance can be measured using a cross-validation set. The high-performing models will then be tested for various random splits of data to ensure consistency in results.
2. **Provide Training sets:** It predicts the value of some output given some input values. The data used to train the DL models consists of records with the output values for various input values. The records are often obtained from historical data.
3. **Building Model:** Building a DL model is an essential step in predicting the anomaly in the data sets. It determines how to make that prediction based on previous examples of input and output data.

The architecture component is a key-value store for DL model metadata. Investing in high- performance, scalable compute, and storage enables the architecture to grow with the needs of the educational organizations. Therefore, the proposed architecture should be able to scale automatically to avoid increases in latency. The proposed architecture supports comprehensive model validation. The DL architecture integrates security measures and governance processes into each layer. It can help mitigate the risk of breaches in data, learning and classification modules, and output.

*Mapping the Architecture to the DL Process*

According to Intel 2018, designing a DL architecture model must consider each step of the DL process in Higher Educational Institutions (HEIs) [6]. The DL architecture must be flexible to adapt to new data sources, handle workloads, and crunch through the massive volume of data. It also needs to consider overarching architecture components that provide security and governance. This architecture is often best to start as the number of DL use cases multiply. Figure 4 shows the comprehensive DL architecture to HEIs.

1. **Data Ingestion:** DL architecture can be built on a massive volume of learning data. It has data ingestion tools that support a wide variety of data sources. These data sources can be structured, unstructured, and semi-structured. The DL architecture is designed to support both batch and stream processing. For stream processing, it needs a fast, reliable, and elastic well-designed data pipeline.
2. **Data Processing:** For the variety of data sources, it requires data transformation, normalization, and cleansing preprocessing techniques. For supervised learning, the architecture should enable the selection of training datasets. It is considered whether data is coming in discrete chunks or continuously. It is also considered throughput and data integration.
3. **Feature Engineering and Data Modeling**: Features turn the inputs into something the algorithms can understand. It might involve simplifying the data, filtering it, or creating new features. Feature selection can be either done manually or automated.
4. **Model Fitting:** A DL model is a mixture of the DL algorithms (random forest, least squares, and logistic regression) and the training dataset. The selection of these algorithms depends on the DL use case. It chooses the appropriate algorithm for trial and error. It is highly dependent on feature and data modeling because an algorithm's performance (accuracy) is affected by the data it runs on. It can also support the user's DL algorithms to suit the user's needs.
5. **Model Training:** The training process uses a training dataset to "educate" the model with the training dataset and the algorithm. It predicts the output from the trained model on the inputs from the training dataset with the actual output values of the training dataset.
6. **Model Validation:** The validation process uses testing datasets to evaluate a trained model. The testing datasets are a separate portion of the same datasets from which the training datasets are derived. The validation techniques are - predictive modeling, training error, test error, and cross-validation.
7. **Deployment:** The execution must be powerful enough to support repeated cycles of experimentation, testing, and tuning. It is considered the given different data, and hence the exact model may behave quite differently.
8. **Monitoring:** The monitoring function can help with model-optimization efforts.

An effective DL solution requires scalability, elasticity, compute power, and low-latency storage. Without this high-performance combination, most DL solutions will not generate optimal business value.

1. **Features:** The DL algorithms primarily use classification tasks that involve decision trees, rule induction, neural networks, and statistical inference. Some of the features identified are generating alerts from data, student groups with similar characteristics, student misuse, lurking, student outcomes, student dropouts, students' low motivation, students' mental health at work, etc.
2. **Dataset:** This DL model uses student's behavior data collected from extracted classes, gates, Wi- Fi usage, library, etc. These data included student background information – gender, status, performance interaction, study status, etc.
3. **Work Flow:** Every entity and stakeholder are in the smart education model is embedded with multiple sensors, capturing the information about itself and its surroundings. Each of these sensors transfers this information for further processing. The data processing module converts the captured data (unstructured) into structured for processing.

There are several steps followed in standardizing the raw data captured by the sensors. These are given below.

1. **Data Source:** There is a large number of sensors that can be installed in educational institutions. It is pertinent to know the data source to avoid any security issues in the smart learning environment.
2. **Data size and type:** It is mandatory to know about the type and size of the data captured by the educational institutions' sensors. It identifies which kind of data the sensor, along with its size, captures.

3. **Data standards:** The data must be handled in different ways. Therefore, choosing the correct data standard for storing and servicing the right type of request is imperative.
4. **Data cleaning:** It removes noise, data outliers, and other non-relevant sections from the smart learning environment's captured data.
5. **Data restructure:** Finally, the data is restructured to remove redundancy and improve data integrity.

After completing the above steps, the sensors' raw data is converted into a standard format, identifiable and accessible by the DL system.

## RESULTS

*Proposed Deep Learning Model*

In smart education, the learning data can be collected and sent to the server automatically. It eliminates the need for any human intervention with the help of sensors. Due to this sensor system, the tedious task of teachers and educators can be minimized. It allows them to concentrate more on teaching and learning, which the primary function of education is. The teachers and educators can use these collected learning data for analytical purposes. A multilayer perceptron algorithm can be employed to establish an efficient and convenient prediction model. The model's accuracy increased as the quantity of data, the number of training cycles, and the model's complexity increased. This algorithm was employed for model training first. The proposed deep learning model consists of input, hidden, and output layers, as shown in Figure 5.

The input layer consists of educational messages, and training is performed with the DL algorithms. All educational data types are taken as input, such as sensor data, library, hostel, wireless, health, security, teaching & learning, and much more. Data integration is performed by collecting all data at one location. After the data collection, the next step is to store the input data into the storage system. After storage, the corresponding tool engine performs the processing of the data. The hidden layer acts as a memory that stores the internal state of the educational data. The memory is updated when the new data arrives, making decisions according to the current and previous input. Then DL techniques are executed, and patterns are identified as output. The obtained result is stored in the storage system. After that, the outcome is visualized in the form of a graphical user interface (GUI), dashboard and decision-making applications.

The input layer comprised neurons of the features, and the output layer produced results with one label. The proportions of the validation and training dataset were set at lower and higher. Each training epoch contained samples with many periods used. These training sessions can be recorded to derive variations in accuracy and loss. In DL, the loss is the value that a neural network tries to minimize. According to the result, the validation data accuracy increased gradually with the number of training sessions being performed; the loss decreased gradually, after which the optimal model was established. Test data are then substituted into the multilayer perceptron model to obtain the predicted results (example, dropout). Using significant variables identified through the analysis as input determined the critical factors fed to the deep neural network to predict learning failure; moreover, prediction performance could be increased.

With this prediction, a platform can be established to help students with substandard academic performance. The teachers and educators should notify the students for whom this applies without attaching labels and providing appropriate assistance in their learning process.

1. **Governance:** The governance layer processes the track data lineage. It maps the existing data flow and develops standard data taxonomies across the HEIs. It plans for metadata collection, integration, usage, and repository maintenance. Data governance reveals source to destination, the various processes and rules involved, and how the data is used.
2. **Security:** Along with data lineage, data security is paramount to a DL architecture. Data security includes authentication, authorization, and encryption. It must apply authentication and access controls across the entire framework, from ingestion to report delivery. In addition, data security measures must be auditable. It encrypts both data at rest and data in transit.

The proposed model's benefits are security & safety, power consumption, attendance management, smart teaching and learning activities, health and hygiene and automated library management.

Educational apps can transform how teaching and learning are done. Educators and administrators are transitioning to student-centered, collaborative environments that appeal to tech-savvy, visual learners. Apart from smart learning analytics, the proposed DL architecture can be used in behavioral systems, content analytics, language translations, healthcare, security and speech recognition

## CONCLUSIONS

The model may be applied in other educational activities, including automatic academic processing, teachers' speech recognition, language translation, social network filtering, students & employee image analysis, material inspection, and game programs. However, some of the challenges of the proposed DL model can be among the following.

1. **Availability:** The availability of data is one of the biggest challenges faced by educational organizations.
2. **Cost:** The cost of the infrastructure can be a significant overhead in small educational institutes.
3. **Data formats:** The data captured by sensors are primarily in different formats.
4. **Data generation:** The sensors embedded in the SLE capture instantaneous information generated at a fast rate. It needs proper storage for data analysis purposes.
5. **Data storage:** The data produced by educational organizations can be massive.
6. **Heterogeneous:** The data produced by the devices are in different types and sizes. A robust system can only handle heterogeneous data types.
7. **Mining data:** The mining of relevant data is one of the primary prerequisites for constructing a helpful classification and prediction model.
8. **Network latencies:** The interconnection of many devices in a network and a large volume of data transactions may lead to network latencies and failures.
9. **Privacy:** The students never want themselves to be monitored, citing personal privacy and other similar factors.
10. **Security:** Security remains the primary concern when handling a large amount of data. It should be addressed effectively in good system architecture.

Educational information is highly available, as well as secured and managed consistently for privacy and liability concerns. Technologies empower administrators and educators, and they have extended the reach of student access to quality education. Interconnection of modern education with environmental, social, and economic issues, and the importance of interdisciplinary thinking and holistic insight, deep learning is particularly relevant in higher education for sustainability.

Smart learning and deep learning algorithms are used to create a smart educational environment. The deep learning model can predict results achieved acceptable accuracy, sensitivity, and specificity in deep learning models. Predictive analytics with deep learning helps the faculty and the parents to get alert and respond appropriately. The presented architecture may facilitate concrete architecture design of use cases in smart learning environments.

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**FIGURES:**

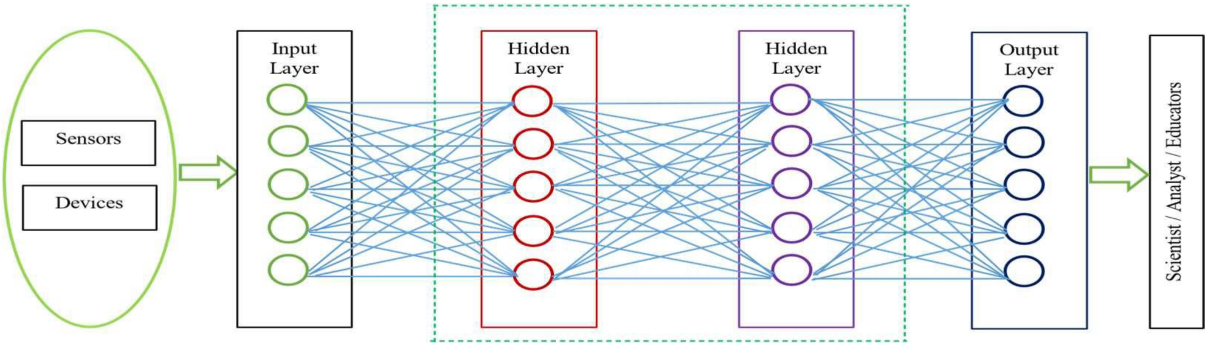


Figure 1: Deep learning Model

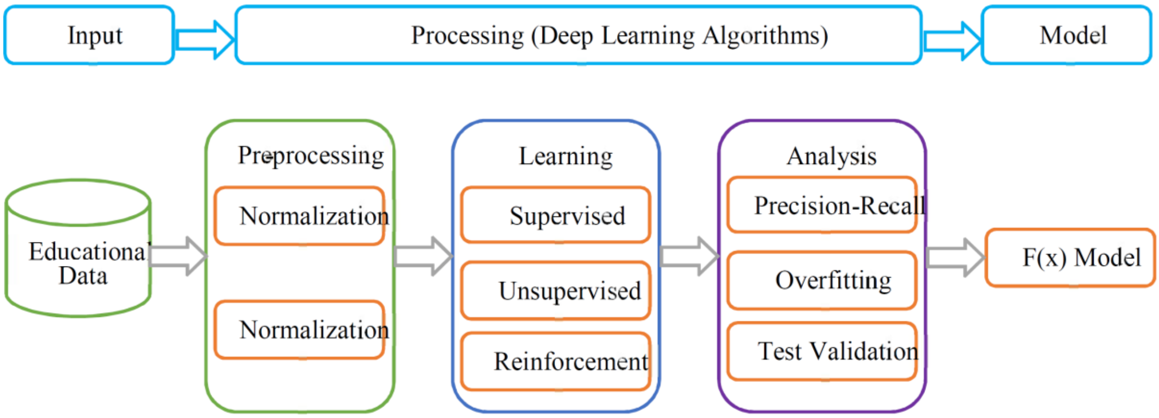


Figure 2: Deep learning computational architecture to educational data

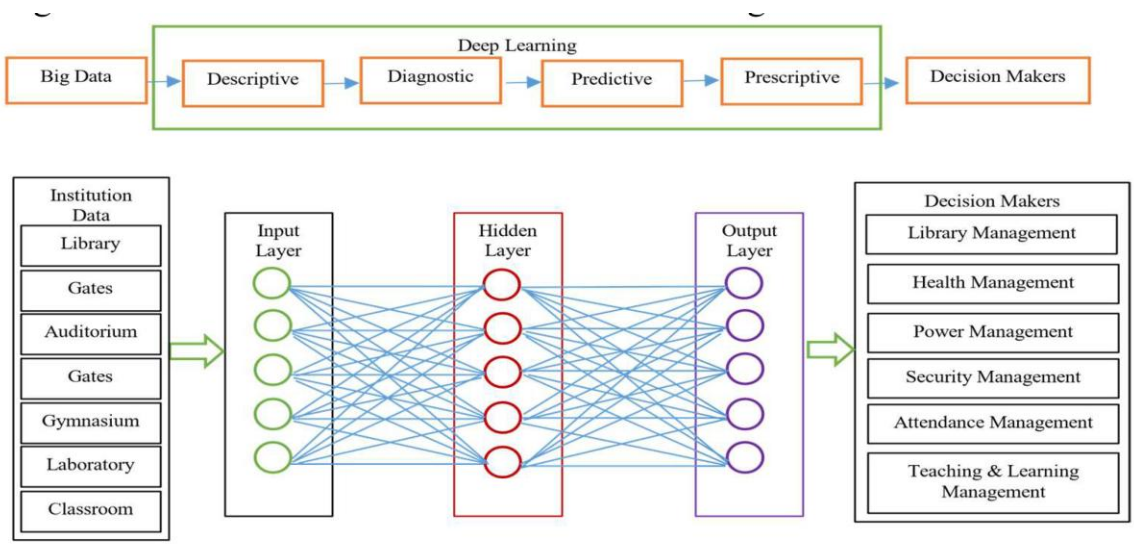


Figure 3: Proposed Deep Learning Model

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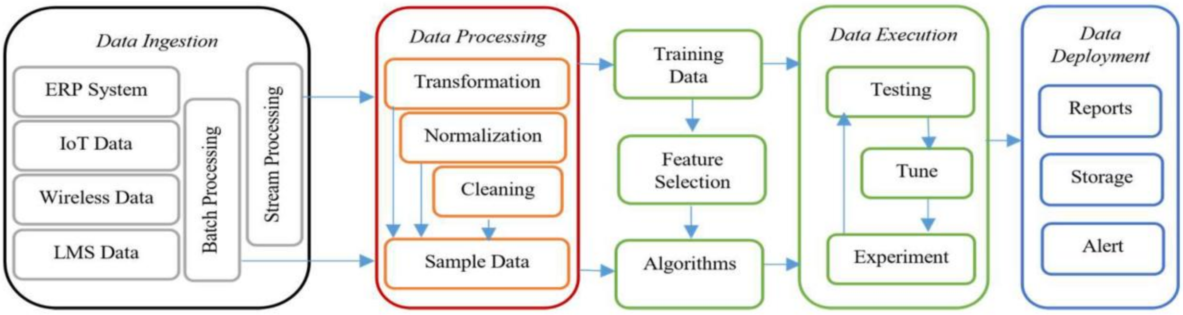


Figure 4:. A comprehensive DL architecture model to HEIs

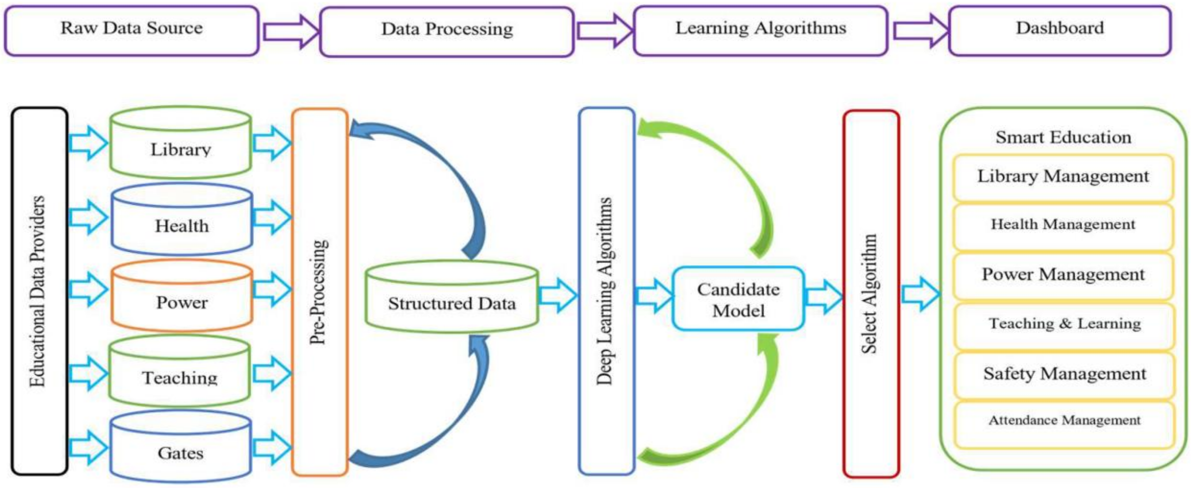


Figure 5: Proposed DL model to smart education analytics