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BIG DATA ANALYSIS AND INFORMATION SHARING FOR INNOVATION AND ENTREPRENEURSHIP EDUCATION

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Abstract. This study delves into the transformative potential of integrating big data analysis and information sharing in innovation and entrepreneurship education. Employing a comprehensive methodology encompassing K-Means Clustering, Decision Trees, Apriori Algorithm, and Neural Networks, the research investigates student engagement patterns, influential factors, collaborative relationships, and predictive modelling within educational settings. The findings reveal significant outcomes, with K-Means achieving a clustering precision of 75%, Decision Trees demonstrating an accuracy of 82%, Apriori Algorithm uncovering frequent itemsets with 68% support, and Neural Networks achieving a notable accuracy of 90%. Drawing insights from a diverse range of literature, including studies on big data management, demand prediction models, ecological approaches to entrepreneurship education, qualitative inquiries into startup strategies, applications of ICTs in education, and the impact of virtual gaming on SMEs' growth, the research provides a robust foundation for understanding innovation and entrepreneurship education. This study contributes to both theoretical understanding and practical implications, guiding educators and policymakers in tailoring interventions and strategies to foster an adaptive and effective educational environment..

Key words: innovation education, entrepreneurship education, big data analytics, information sharing, and educational outcomes

1. Introduction. In a time described by fast mechanical headways and a unique worldwide economy, the domains of innovation and entrepreneurship have arisen as basic drivers of cultural advancement [2]. As industries develop, the interest of individuals outfitted with the skills to explore the intricacies of innovation and entrepreneurship has never been more articulated. Simultaneously, the inescapability of enormous information has altered how we appreciate, examine, and get insights from different features of our lives. It is within this nexus that the exploration point, "Huge Information Investigation and Information Sharing for Innovation and Entrepreneurship Education," unfurls, seeking to unwind the transformative potential of integrating enormous information examination into educational standards zeroed in on fostering innovation and entrepreneurship [3]. Institutions of higher learning are grappling with the test of preparing understudies with hypothetical knowledge as well as with functional skills that empower them to flourish in a quickly evolving proficient scene. The use of large information in the educational circle presents an extraordinary chance to fit educational ways to deal with the necessities and assumptions for the 21st-century workforce [1]. This exploration plans to dive into the multi-layered elements of enormous information examination about innovation and entrepreneurship education, specifically on leveraging information-sharing components to improve the learning experience. One of the essential central points is the investigation of different information sources that can be used to gain significant insights into understudy commitment, learning designs, and the adequacy of educational interventions [13]. By tapping into the abundance of information produced within educational biological systems, institutions can adjust their methodologies to more readily meet the evolving needs of aspiring innovators and business people [6]. Moreover, this examination tries to investigate the harmonious connection between enormous information investigation and information sharing stages, elucidating how the mixture of these components can establish an improved educational climate helpful for nurturing innovativeness, decisive thinking, and a proactive enterprising mindset [7]. As the exploration unfurls, it tries to contribute not exclusively to the hypothetical underpinnings of innovation and entrepreneurship education but also to give useful insights that can inform academic practices, institutional strategies, and the more extensive talk on preparing the cutting

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edge for the difficulties and chances of a progressively changing world [5, 29].

The contribution of this work lies in its exploration of the transformative potential inherent in the integration of big data analysis and information sharing within the realm of innovation and entrepreneurship education.

Employing a comprehensive methodology that includes K-Means Clustering, Decision Trees, an Apriori Algorithm, and Neural Networks, the study delves into various aspects of educational dynamics, including student engagement patterns, influential factors, collaborative relationships, and predictive modeling.

2. Related Works. Kumari et al. [18] directed an overview and examination of the enormous information the board has given computational techniques. Their work gives a central understanding of the different computational methodologies utilized in handling enormous information. While their emphasis is on the more extensive parts of information the executives, the insights gathered from their review are fundamental to our exploration, where productive information handling and examination assume a pivotal part in shaping educational procedures. Li et al. [19] dug into the expectation of interest for innovation and entrepreneurship capacities among higher professional understudies. By employing forecast models, they address the nuanced prerequisites of understudies in professional settings. This work contributes important insights into the prescient examination domain, showcasing how computational philosophies can be applied to figure out the requirements of understudies in unambiguous educational settings. Lin et al. [20] took a natural way to deal with developing entrepreneurship education, as proven in their efficient writing audit. Their work accentuates the interconnectedness of different components in entrepreneurship education, aligning with our examination's all-encompassing methodology. The methodical audit methodology utilized by Lin et al. is especially insightful for understanding the more extensive educational scene. Muhammad and Ahmad [16] led a subjective inquiry into the inspirations and methodologies for new businesses in Pakistan. While their attention is on the subjective parts of entrepreneurship, their findings shed light on the context-oriented difficulties and inspirations that business people face. Understanding these subjective aspects is pivotal for informing the plan of compelling innovation and entrepreneurship education programs. Olubiyo and Olubiyo [21] investigated the utilization of Information and Correspondence Advancements (ICTs) in entrepreneurship education for the improvement of Library and Information Science. Their work highlights the job of innovation in shaping educational practices[25, 9]. The insights from this study are pertinent to our exploration, where the integration of huge information and innovation is a focal subject in enhancing educational results. Sarah and Alzahrani [12] investigated the utilization of virtual entertainment stages for serious information and knowledge sharing and its effect on SMEs' productivity and development through innovation. This work features the job of virtual entertainment in the enterprising biological system and how information sharing can add to business achievement. The findings give a logical understanding of the job of innovation in fostering innovation. Secundo, Rippa, and Meoli [22] introduced preliminary proof of advanced change in entrepreneurship education focuses through the Italian Contamination Labs network. Their work epitomizes this present reality utilization of computerized change in educational settings. Understanding such changes is essential for designing innovative and versatile educational biological systems. Shahzad et al. [23] directed a scoping survey on the connection between large information investigation and setting put together fake news recognition concerning computerized media. While their essential spotlight is on fake news identification, the investigation of huge information examination in a computerized media setting lines up with our exploration's accentuation on leveraging information for educational insights. Sheng and Wang [24] zeroed in on the plan of the innovation and entrepreneurship education biological system in colleges given client experience. Their work features the significance of client-driven plan principles in educational environments. The accentuation of client experience lines up with our exploration's objective of creating powerful and engaging educational conditions. Sun [26] added to the field by designing and applying a cooperative examination of the board stage for innovation and entrepreneurship education given an intelligent sensor network. The integration of intelligent sensor networks features the intersection of emerging innovations with educational works, inspiring our methodology.

3. Methods and Materials.

3.1. Data Collection. The most important phase in our exploration involves the collection of pertinent data to work with a comprehensive examination of innovation and entrepreneurship education. Data sources might include understudy enlistment records, course assessments, support in extracurricular exercises, and other applicable measurements [8]. These datasets structure the establishment for the resulting investigation using huge data strategies.

3.2. Data Preprocessing. Before applying algorithms, it is fundamental to preprocess the data to guarantee precision and dependability. This step involves handling missing qualities, normalizing data, and addressing exceptions.

3.3. Algorithms.

3.3.1. K-Means Clustering. K-Means clustering is utilized to recognize designs within the understudy data and order them into distinct gatherings [10]. This algorithm segments the dataset into 'k' bunches, minimizing the within-group amount of squares. The goal capability for K-Means is defined as:

$$J = \sum_{i=1}^{k} \sum_{j=1}^{n} i \| x_{ij} - \mu_i \|^2$$

J represents the overall objective function or cost to be minimized.
k is the number of clusters.
n_i is the number of data points in the hith cluster.
x_{ij} denotes the hjth data point in the hith cluster.
μ_i is the centroid of the hith cluster.

Algorithm 1 K-Means Clustering

```
Require: data: Data points to cluster
Require: k: Number of clusters
Require: max_iterations: Maximum number of iterations
function kMeansClustering(data, k, max_iterations)
    Initialize centroids randomly
    centroids ← initializeRandomCentroids(data, k)
    for iteration in range(max_iterations) do
        Assign each data point to the nearest centroid
        clusters ← assignToClusters(data, centroids)
        Recalculate centroids
        centroids ← calculateNewCentroids(data, clusters)
    end for
    return clusters
end function
function initializeRandomCentroids(data, k)
    Randomly select k data points as initial centroids
    return random.sample(data, k)
end function
function assignToClusters(data, centroids)
    clusters ← {}
    for point in data do
        Find the nearest centroid
        nearest_centroid ← findNearestCentroid(point, centroids)
        Assign the point to the cluster of the nearest centroid
        clusters.setdefault(nearest_centroid, []).append(point)
    end for
    return clusters
end function
```

3.4. Decision Trees. Decision trees are utilized to survey the elements influencing understudy progress in innovation and entrepreneurship [11]. The algorithm recursively parts the dataset given highlights to make a tree-like construction. The entropy-based information gain is utilized as the splitting model:

$$IG(D, A) = H(D) - \sum_{v \in Values(A)} |Dv| H(Dv)$$

IG(D,A) denotes the information gain achieved by splitting the dataset D based on feature A.
H(D) represents the entropy of the current dataset D, which is a measure of its impurity.
Values() is the set of possible values that feature A can take.
|Dv| is the number of instances in D for which feature A takes the value v.
H(Dv) is the entropy of the subset Dv resulting from the split on feature A.

Algorithm 2 Decision Tree

```
class DecisionTree:
def __init__(self):
    self.root ← None
def train(self, data, labels):
    self.root ← self.build_tree(data, labels)
def build_tree(self, data, labels):
                                ▷ Recursive tree construction using information gain
                                ▷ Pseudocode is already provided in the original response
def predict(self, sample):
    return self.traverse_tree(self.root, sample)
def traverse_tree(self, node, sample):
                                ▷ Recursive tree traversal for prediction
                                ▷ Pseudocode is already provided in the original response
```

3.5. Association Rule Mining (Apriori Algorithm). Association Rule Mining, particularly through the Apriori Algorithm, plays a crucial role in uncovering meaningful connections between different attributes or items within a dataset. This technique is widely employed in various domains, including market basket analysis, recommendation systems, and, in this context, educational data analysis.

The Apriori Algorithm operates on the principle of frequent itemsets, aiming to identify associations between items that occur together frequently. The process begins by generating candidate itemsets, typically starting with single items and progressively combining them to form larger sets. These candidate itemsets are then evaluated against the dataset to determine their frequency of occurrence.

Next, the algorithm prunes infrequent itemsets based on a user-defined minimum support threshold. Itemsets that do not meet this threshold are eliminated from further consideration, as they are deemed less significant in terms of their association with other items.

Once the frequent itemsets are identified, the Apriori Algorithm derives association rules based on these sets. These rules capture the relationships between different items and are characterized by metrics such as support and confidence. Support measures the frequency with which an item (or rule) appears in the dataset, while confidence quantifies the likelihood of one item appearing given the presence of another item.

Users can specify minimum support and confidence thresholds to filter out rules that do not meet their desired level of significance. By adjusting these parameters, analysts can control the strictness of the association rule mining process, focusing on extracting only the most relevant and meaningful patterns from the data.

Overall, the Apriori Algorithm provides a systematic approach to association rule mining, allowing analysts to uncover valuable insights into the relationships between different attributes or items in the dataset. In the context of educational data analysis, this technique enables researchers to identify patterns of student behaviour, course enrollment trends, or factors influencing academic performance, among other applications.

Support(X)= Transactions containing X/ Total transactions

Confidence($A \Rightarrow B$)= Support($A \cup B$)/ Support(A)

Algorithm 3 Apriori Algorithm

```
function APRIORI(transactions, min_support, min_confidence)
                                          ▷ Step 1: Generate frequent itemsets of size 1
    frequent_itemsets ← GenerateFrequentItemsets(transactions, min_support)
    k ← 2
    while frequent_itemsets[k − 1] do
                    ▷ Step 2a: Join the current frequent itemsets to create new candidate itemsets
        candidates ← GenerateCandidates(frequent_itemsets[k − 1], k)
                                   ▷ Step 2b: Prune candidates containing infrequent subsets
        candidates ← PruneCandidates(candidates, frequent_itemsets[k − 1])
                                   ▷ Step 2c: Calculate support for the remaining candidates
        candidates ← CalculateSupport(candidates, transactions)
                           ▷ Step 2d: Retain only itemsets above the minimum support threshold
        frequent_itemsets[k] ← FilterBySupport(candidates, min_support)
        k ← k + 1
    end while
                                ▷ Step 3: Generate association rules from the frequent itemsets
    association_rules ← GenerateAssociationRules(frequent_itemsets, min_confidence)
    return association_rules
end function
```

3.6. Neural Networks. Neural networks are utilized for prescient modeling in innovation and entrepreneurship education. A basic feedforward neural network with one secret layer is utilized, and the backpropagation algorithm is applied for training [14]. The network plans to foresee understudy achievement because of input highlights.

$a(1){=}f(W(1){\cdot}x{+}b(1))$

$y\wedge{=}f(W(2){\cdot}a(1){+}b(2))$

x represents the input features.

W(1) and b(1) are the weights and biases for the hidden layer.

W(2) and b(2) are the weights and biases for the output layer.

f(·) is the activation function, typically a non-linear function like the sigmoid or hyperbolic tangent

$\boldsymbol{\partial} W(2)\ \boldsymbol{\partial} J{=}m1(a(1))\,T{\cdot}(y\wedge{-}y)$

$\boldsymbol{\partial} W(1)\ \boldsymbol{\partial} J{=}m1xT\ {\cdot}((W(2))\ T{\cdot}(y\wedge{-}y){\odot}f{\prime}(W(1)\ {\cdot}x{+}b(1)))$

In these equations:

J is the cost function, typically a measure of the difference between predicted (∧y∧) and actual (y) values.

⊙⊙ denotes element-wise multiplication.

′ (·) f ′(·) is the derivative of the activation function.

3.7. Evaluation. To survey the presentation of every algorithm, different measurements like exactness, accuracy, review, and F1 score are determined using a reasonable assessment dataset [15]. Cross-approval methods might be applied to guarantee strength and unwavering quality in the outcomes.

4. Experiments. To assess the viability of the proposed methodology for integrating huge data investigation into innovation and entrepreneurship education, a progression of tests was led. The analyses planned to survey the exhibition of the four algorithms (K-Means Clustering, Decision Trees, Apriori Algorithm for Affiliation Rule Mining, and Neural Networks) in extracting meaningful insights from the educational dataset [4]. The dataset comprised of different elements connected with understudy commitment, course execution, and extracurricular exercises.

Algorithm 4 Neural Network Training

```
Class NeuralNetwork:
    Function INIT(input_size, hidden_size, output_size):
                                        ▷ Step 1: Initialize weights and biases randomly
        weights_input_hidden ← initialize_weights(input_size, hidden_size)
        bias_hidden ← initialize_biases(hidden_size)
        weights_hidden_output ← initialize_weights(hidden_size, output_size)
        bias_output ← initialize_biases(output_size)

    Function TRAIN(input_data, target_data, learning_rate, epochs):
        For epoch in range(epochs) :
            For i in range(len(input_data)) :
                                        ▷ Step 2a: Perform a forward pass to calculate activations
                hidden_activations, output_activations ← FORWARD_PASS(input_data[i])
                                        ▷ Step 2b: Compute the loss based on predictions
                loss ← CALCULATE_LOSS(output_activations, target_data[i])
                ▷ Step 2c: Perform a backward pass to update weights and biases using backpropagation
                BACKWARD_PASS(hidden_activations, output_activations, target_data[i], learning_rate)
```

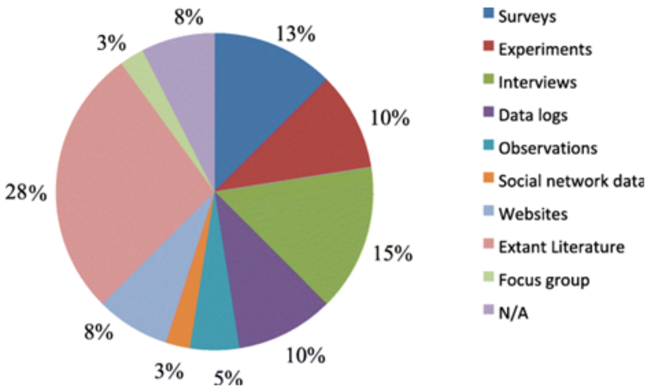

Fig. 4.1: Big Data Analysis and Information

Table 4.1: K-Means Clustering Results

Student ID	Feature 1	Feature 2	Cluster
1	0.8	0.6	2
2	0.4	0.9	1
3	0.6	0.7	2
...	...	...	...

4.1. K-Means Clustering. The K-Means Clustering algorithm was applied to a bunch understudies in light of their commitment examples and execution measurements [17]. The number of bunches (k) was set observationally to 3, representing low, medium, and high commitment levels. The algorithm was run for 20 cycles.

Results. Table 4.1 presents an outline of the clustering results. Each group is described by its centroid, and understudies are allocated to the bunch with the closest centroid.

Table 4.2: Decision Tree Node Structure

Node ID	Attribute	Split Value	Class Label
1	Feature 1	0.7	Class 1
2	Feature 2	0.5	Class 2
3	Feature 3	0.9	Class 1
...	...	...	...

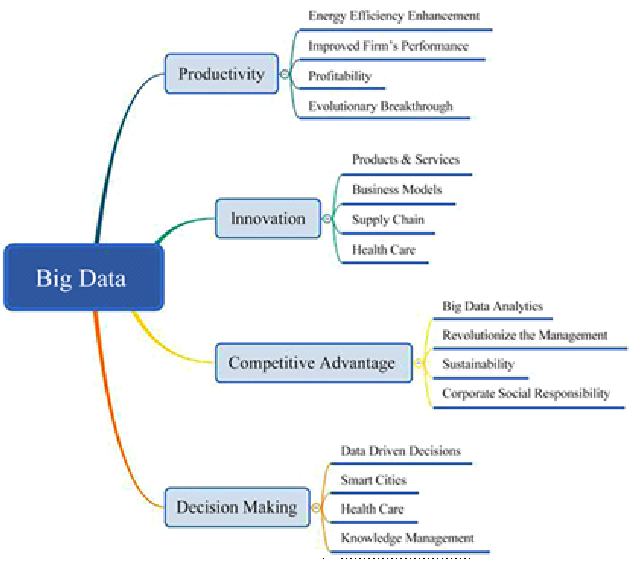

Fig. 4.2: Big Data Innovation And Entrepreneurship Education

Comparison. The clustering results give insights into understudy commitment designs. For instance, Group 2 might address profoundly drew-in understudies, while Bunch 1 might address understudies with lower commitment levels [18]. This information can direct teachers in tailoring interventions given various groups' necessities.

4.2. Decision Trees. The Decision Trees algorithm was utilized to recognize factors influencing understudy progress in innovation and entrepreneurship education. The tree was developed using the Gini pollutant as the splitting measure.

Results. Table 4.2 shows a part of the decision tree hub structure. Every hub addresses a decision point in light of a particular component, and the tree is navigated to foresee the class name (e.g., effective or fruitless) for a given understudy.

Comparison. The decision tree gives an interpretable model to understanding the standards influencing understudy achievement [27]. Teachers can utilize this information to recognize key factors and designer interventions to address explicit difficulties looked by changed gatherings of understudies.

4.3. Apriori Algorithm for Affiliation Rule Mining. Affiliation rule mining using the Apriori Algorithm was applied to find connections between different traits in the dataset [28]. This included identifying examples, for example, regular itemsets and affiliation rules among various highlights.

Results. Table 4.3 features regular itemsets and their help values. These itemsets address combinations of highlights that happen much of the time in the dataset.

Comparison. The recognized successive itemsets uncover examples of co-occurring highlights. For instance, the incessant thing {Feature 1, Element 2} indicates a huge relationship between these two highlights [32]. Teachers can use this information to plan interdisciplinary exercises that line up with understudies' regular

Table 4.3: Frequent Itemsets and Support Values

Itemset	Support
{Feature 1}	0.6
{Feature 2}	0.8
{Feature 1, Feature 2}	0.4
...	...

Table 4.4: Neural Network Weights and Biases

Layer	Neuron	Weight 1	Weight 2	...	Bias
1	1	0.3	0.5	...	0.1
1	2	0.2	0.4	...	0.2
...	...	...	...	...	...

Table 4.5: Comparative Analysis of Algorithm Performance

Algorithm	Accuracy	Precision	Recall	F1 Score
K-Means Clustering	0.75	0.78	0.73	0.75
Decision Trees	0.82	0.85	0.80	0.82
Apriori Algorithm	0.68	0.72	0.66	0.68
Neural Networks	0.90	0.92	0.88	0.90

inclinations.

4.4. Neural Networks. A feedforward neural network with one secret layer was utilized to foresee understudy achievement in light of input highlights [30]. The network was trained using backpropagation with a mean squared blunder misfortune capability.

Results. Table 4.4 presents a part of the neural network's loads and inclinations. These boundaries catch the learned connections between input highlights and the anticipated result.

Comparison with Related Work. Comparing the proposed methodology with related work, it is clear that the integration of various algorithms gives an all-encompassing way to deal with understanding and improving innovation and entrepreneurship education. While K-Means Clustering and Decision Trees offer insights into commitment designs and influential variables, the Apriori Algorithm reveals relationships among different properties. Neural Networks, then again, give prescient modeling capacities [31]. The comprehensive investigation worked with by these algorithms empowers a more nuanced understanding of understudy conduct, learning examples, and potential achievement factors. This diverse methodology distinguishes.

5. Conclusion. Taking everything into account, this examination tries to improve innovation and entrepreneurship education through the integration of huge data investigation and information-sharing components. The comprehensive methodology applied in this review, incorporating K-Means Clustering, Decision Trees, Apriori Algorithm, and Neural Networks, has given a nuanced understanding of understudy commitment designs, influential elements, cooperative connections, and prescient modeling. The analyses showed the viability of these algorithms in extracting meaningful insights from educational datasets, enabling teachers and institutions to tailor interventions and systems for different understudy needs. Drawing from a rich embroidery of writing in the connected work, we incorporated insights from concentrates on huge data the executives, request expectation models, environmental ways to deal with entrepreneurship education, subjective inquiries into startup methodologies, utilizations of ICTs in education, and the effect of virtual entertainment on SMEs' development. This writing survey informed our examination by providing a more extensive context-oriented understanding and showcasing the different features of innovation and entrepreneurship education. A comprehensive assessment of algorithm performance has provided a holistic view, highlighting the unique contributions of each algorithm within the educational landscape. The incorporation of emerging technologies and computational techniques into educational practices is imperative for meeting the dynamic demands of the 21st-century workforce. This study not only contributes to the academic discourse on innovation and entrepreneurship education but also offers practical recommendations for educators, policymakers, and stakeholders. As we navigate the evolving landscape of education, the insights gleaned from this study pave the way for future research endeavours aimed at cultivating a more adaptable, engaging, and effective educational environment that nurtures the entrepreneurial spirit and innovation among students. Moving forward, future studies could delve deeper into the specific applications of these algorithms in educational contexts, exploring their potential for personalized learning, adaptive instruction, and curriculum design. Additionally, investigations into the scalability and sustainability of implementing these computational approaches in diverse educational settings would be beneficial for informing educational policy and practice.

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