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Navigating Ethics in Digital Humanities: A Deep Dive into Decision Distribution within Higher Education at the University of Jordan

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Abstract— This research aims to aid higher education institutions in making decisions that align with student needs and enhance their satisfaction. It considers decision presentation, timing of implementation, and communication of the benefits tied to educational quality improvements. To gauge student opinions, an online questionnaire research design was adopted, involving 3,000 male and female students from the University of Jordan. Findings indicated that students generally express dissatisfaction with higher education decisions and regulations due to unclear communication and limited implementation time.

For predicting educational quality outcomes, four machine learning algorithms were employed, each corresponding to four different higher education decisions. Notably, the Random Forest (RF) algorithm showcased superior performance. In the initial questionnaire, it achieved an accuracy of 97%, which slightly decreased to 92% in the second questionnaire due to the expanded dataset and varying factors affecting accuracy. The k-Nearest Neighbors (KNN) algorithm also yielded impressive results, achieving a remarkable 94% accuracy in the third questionnaire.

In the third questionnaire, the Decision Tree (DT) algorithm exhibited an accuracy of 85% in optimal scenarios. In contrast, the Convolutional Neural Network (CNN) algorithm, tailored for intricate tasks with numerous variables, consistently performed below expectations across all questionnaires. Its efficacy consistently lagged alternative algorithms, indicating a misalignment with the specific demands of its operational framework.

Keywords- Ethics, Digital Humanities, Machine Learning, Higher education, Convolutional Neural Network.

I. INTRODUCTION

Sentiment analysis, also known as opinion mining, is a growing field of great value due to the rise of the internet and technological progress. This has led to a surge in data volume and empowered people to share opinions on social media platforms. Such data offers opportunities for analysis in education to enhance learning experiences. Sentiment analysis extracts opinions, whether subjective or outcome-based, and plays a pivotal role in informed decision-making for better educational outcomes. Despite the challenge of navigating opinion-rich websites, the need for automatic sentiment analysis systems is increasing. Startups and organizations are focusing on sentiment analysis services, driven by its practical applications. This study aims to assess student and faculty opinions on higher education decisions, predicting their impact and improving educational outcomes.

"Big Data" encompasses research datasets, including online social network data, and behavioral observations. Artificial intelligence can shape policies, expanding perspectives. The lack of student participation in university decisions and legislation may marginalize important issues. Electronic data evolution requires insights for teachers, students, and education.

Natnography, a method of exploring online communities, aids in qualitative social network analysis. This study applies Netnography to understand student and faculty opinions, improving decision-making and reducing psychological burdens.

This Paper aims to enhance decisions by analyzing student and faculty opinions, employing Netnography and ethical considerations. The research methodology includes processes like redefining research questions, community identification, data collection, interpretation, and analysis. Ethical considerations involve transparency, confidentiality, feedback incorporation, and informed consent.

II. Background And Literature Review

A. *Background*

1) *Digital Humanities (DH)*

In the Renaissance era, the term "humanities" was introduced by Italian scholars, signifying a shift towards valuing human perspective as the standard for all matters. Humanities encompass fields like literature, philosophy, arts, architecture, music, theatre, and dance, expressing human culture. Understanding digital formats, binary code, and digital materials is crucial for comprehending digital environments [5].

Digital Humanities (DH) emerged through collaborative digital projects and encompasses various disciplines, evolving [14].

DH involves converting diverse subjects into digital formats for accessibility and collaboration. It involves analyzing, investigating, and presenting information electronically [11]. DH is an interdisciplinary field that explores the interplay between computing and humanities, involving systematic study, research, and presentation of information. It assesses how digital media influences different disciplines and their contributions to computing knowledge.

DH can refer to both a social movement and an academic field, where technology enhances humanities teaching and research. The availability of affordable apps enables tasks that were previously impossible without advanced computing power. DH applications include visualization, communication, data retrieval, storage, and multimedia use. DH projects range from small-scale initiatives to large, collaborative endeavours involving multiple institutions [3].

2) *Netnography*

This paper aims to utilize the Netnography methodology, a novel research approach coupled with big data analysis, particularly suited for studying digital communities and cultures. Netnography, also known as online ethnography, involves adapting ethnographic techniques to digital contexts. It's a specialized form of ethnographic research focused on online interactions and virtual societies [2].

A) Importance of Netnography: Netnography is recognized for exploring online communities and interactions, offering qualitative insights into social network analysis [2]. It encompasses various forms of data like text, graphics, and multimedia [9]. Derived from ethnography, it involves techniques such as interviewing, discussion analysis, and observation[7]. Netnography's research process involves stages like meditation, investigation, data collection, and analysis, among others [2]. Kozinets pioneered this approach due to evolving online social interactions [8].

B) Advantages of Netnography: Netnography offers easy data transcription from online sources and has low data access costs. It grants constant data availability and can cover global perspectives. Moreover, it's unobtrusive and doesn't disturb online community members. It's particularly useful when studying phenomena on a global scale [2].

Over the past two decades, researchers, including Kozinets, have embraced online ethnographic research (Netnography), especially for virtual communities[8. Netnography diverges from traditional ethnography by collecting data through online interactions. It centers on studying interactions, consumer discussions, and online communities, benefiting from digital data[8]. The methodology emphasizes ethical practices, data analysis, and interpretations[9].

The research methodology employs Netnography methods and practices, involving steps like redefining research questions, community identification, digital observation, ethical considerations, data interpretation, and representation of results.

3) *The Phenomenology of Internet Communication Technology (ICT)*

According to [2], certain phenomena have introduced a multidisciplinary approach that employs internet-based communication technologies to engage fields like philosophy, social psychology, informatics, and political science. This approach is applied within conflicts to guide societies towards democracy and moderate reconciliation. ICT (Information and Communication Technology) is utilized to shift intergroup intentions during conflicts, transitioning from animosity to reconciliation and moderation. This process aims to drive social change, leading from conflict to reconciliation and eventual societal transformation. The purpose is to establish an effective ICT platform that offers measurement tools and understanding, positively impacting social groups involved in or affected by political conflicts. This signifies the integration of digital transformation into human affairs.

The utilization of Internet communication technologies, as highlighted by [2], holds promise for fostering reconciliation in current and future societies. This potential extends to various aspects like economic reconciliation, social reconciliation, and the formulation of public policies for societal development. Such endeavours can boost motivation for societal growth, ultimately leading to prosperous and truth-driven societies. In this context, digital humanities emerge as a powerful tool, leveraging ICT to fortify democratic governance and civil society institutions while facilitating the transmission of public policies.

4) Big Data:

Big data, a term coined by John Mashey in [10], refers to the analysis and handling of vast or complex datasets beyond the capabilities of traditional data processing tools. It involves data sets that exceed common software's capacity to manage, capture, and process them effectively. The challenges of big data encompass data capture, analysis, storage, transfer, privacy, and more. The term is characterized by three key concepts: variety, velocity, and volume. It's associated with advanced analysis methods like user behavior analysis and predictive analytics to extract insights from large datasets. Big data applications have expanded with the growth of data collection devices such as IoT devices, mobile devices, and sensors.

5) Machine Learning (ML):

Machine learning, part of artificial intelligence, involves computer algorithms that learn and make decisions autonomously by recognizing patterns in data. It allows computers to improve without explicit programming, making decisions based on learned patterns from data. Machine learning algorithms build models from training data to make predictions or decisions without being explicitly programmed. Different types of machine learning include supervised learning (with labelled training data) and unsupervised learning (without guidance).

6) Data Mining (DM):

Data mining converts raw data into valuable information by identifying patterns within large datasets. It uses methods from statistics, machine learning, and database systems to uncover trends and patterns for various applications like marketing strategies and fraud detection. Data mining is part of the "knowledge discovery in databases" process and helps build machine learning models for applications such as recommendation systems and search engines.

7) Online Social Data:

Online social data collection involves gathering user information from platforms like Facebook, LinkedIn, and Twitter for advertising or analysis purposes. Data includes sociodemographic details, interests, and activities. Online social media platforms and third-party entities use this data for advertising. Social data analysis involves collecting and analyzing data to extract insights and understand factors like impact and relevance, often in real-time. However, concerns regarding privacy and usage arise with the utilization of social data.

Overall, these sections introduce and explain concepts like big data, machine learning, data mining, and the analysis of online social data. These technologies have diverse applications and implications, ranging from improving business strategies to understanding user behavior on online platforms.

B. LITERATURE REVIEW

This section delves into significant works related to the research study, starting with an

Netnography, introduced by marketing researcher Robert V. Kozinets, is a qualitative research methodology focusing on online accounts shared by individuals[8, 9,]. Positioned within qualitative research methodologies, Netnography merges the realms of the internet and ethnography [7].

In a systematic literature review by Alfayomi et al. (2021), Netnography is explored as a method adapting ethnographic techniques to study societies through computer communication, particularly in marketing research. The study investigates the ethical exercises of Netnography in information systems (IS). Findings reveal that ethical practices in Netnography are evolving, with differing perspectives on fair and unfair methods.

The Study in [4] contribute by discussing the implications of broadening the definition of Netnography in qualitative research. The study emphasizes the need for active participation in Netnography, challenging the idea that non-participatory techniques ensure objectivity.

In [6] highlight Netnography's potential in providing service companies with unique access to authentic customer data online. The paper serves as a guide for service managers, outlining applications in service innovation, advertising, and environmental research.

In [19] employs a narrative literature review to examine Netnography's application in exploring online communities among older individuals. The study reveals a prevalence of Netnography in leisure studies but a relatively limited application in digital technology.

In [20] study explores the growing use of the internet as a research method, emphasizing Netnography's acceptance across diverse fields. The conclusion suggests that scholars in media studies and mass communication should consider employing the Netnographic research methodology.

Moving on to Digital Humanities, the literature explores research methodologies and applications.

Zhang et al.'s research [13] assesses qualifications in job advertisements using digital humanities tools. The study utilizes CSl2, VOSviewer, and Pajek to analyze word frequencies and proposes a collaborative digital humanities project involving academic librarians, IT technicians, and international scholars.

Th estudy in [21] focus on exploring historical events through digital humanities. Their research introduces a radiological model to visualize event-based networks, providing a comprehensive and engaging representation of historical interconnectedness.

In the realm of students' perspectives on decisions and legislation, multiple studies offer insights.

The study in [22] examine student participation in decision-making, revealing a misalignment between students' opinions and actual practices. The authors in [23] establish a strong connection between students' overall satisfaction and their reported learning and development in representative roles, emphasizing the importance of acknowledging students' learning agendas.

Studies by Zhang et al.[13] introduce predictive techniques such as clustered KNN, Exercise-Enhanced Recurrent Neural Networks (EERNN), and smart CNN traffic forecasting applications. These models demonstrate resilience to noisy data, forecast student performance, and classify data, achieving notable accuracy rates.

In [15] emphasize the importance of considering students' development, performance, and potential in determining learning objectives. Their proposed Back Propagation Neural Network (BP-NN) model provides analytical tools for estimating student performance based on various characteristics.

The study in [16] addresses the pressing challenge of traffic congestion in Amman, Jordan, using a dynamic approach. By integrating social media, artificial intelligence, and decision support, the goal is to enhance traffic prediction and alleviate congestion. Direct engagement with social media users and the utilization of the TRF2021JOR dataset aim to streamline predictions, ultimately contributing to economic development and social stability in Jordan.

The study in[17] delves into sentiment analysis and opinion polling in online education. Using a qualitative descriptive research method, it aims to identify and visualize students' feelings in university Facebook groups. Findings show 39.7% positive and 52.3% negative sentiments, emphasizing the importance of understanding these emotions for the online learning environment.

The study I [18] ranks principles for effective online education in Jordanian higher institutions. Through an online survey, perspectives from 6500 participants were gathered, revealing positive experiences and success in online education. The study introduces three algorithms to predict its extent, marking a novel approach in this research domain.

III. Research Methodology

In this section, the methods used to achieve the desired results will be explained. The focus is on understanding the opinions of students and faculty members regarding decisions and legislation from the Ministry of Higher Education and Scientific Research. The methodology employed, steps taken, data collection, pre-processing, and ethical considerations are detailed.

1) Netnography Methodology:

The study employs the Netnography methodology, an approach combining online ethnography to examine internet-based societies and cultures. Netnography is known for exploring and analyzing online communities, even with large datasets. It allows for qualitative insights through various forms of data like text, images, and more. Kozinets highlights the advantages of Netnography, such as maintaining researcher objectivity, analyzing small and big data, and focusing on specific online behaviors.

2) Questionnaire and Data Collection:

Irrespective of the field of research, the initial and paramount phase in any research endeavour is data collection. Depending on the subject area and the specific data requirements, various methodologies for data collection are employed. For this study, data concerning students was procured from the University of Jordan.

Established in 1962, The University of Jordan is a non-profit institution located in Amman, the capital of Jordan, specifically in the Jubaiha region. The university boasts a wide array of academic programs, with 250 offerings spread across 24 colleges encompassing diverse disciplines. For those pursuing advanced degrees, the university provides 111 master's programs and 38 doctoral programs. Over its history, the institution has awarded degrees to more than 200,000 graduates worldwide. The university has earned recognition on a global scale, being ranked among the top 500 universities worldwide according to the QS global rankings. This information is derived from the official university website.

Data about the perspectives of both students and faculty members regarding decisions and regulations issued by the Ministry of Higher Education and Scientific Research were collected through the utilization of questionnaires.

A questionnaire is a set of printed or written queries with multiple-choice answers, designed to conduct a survey or statistical analysis. In this study, we adhered to the ethical considerations of the Netnography questionnaire while gathering data from students.

Four distinct questionnaires were created to gather insights into the viewpoints of university students in Jordan regarding the following topics:

- The decision made by the Ministry of Higher Education and Scientific Research concerning the standardization of semester-hour limits for bachelor's students across all universities and university colleges.
- The implementation of the grading scale system for evaluating students.
- The decision by the Ministry of Higher Education and Scientific Research to discontinue the administration of English language level exams in the language centers at official Jordanian universities, restricting them solely to internationally recognized English language exams.
- The Ministry of Higher Education and Scientific Research's policy aimed at enhancing the university's relationship with students' parents.

3) Dataset

The study collected data from 3,000 students at the University of Jordan to analyze opinions on decisions and legislation. This dataset is used to predict the effectiveness of decisions and propose improvements.

4) Proposed Algorithms

This section introduces the supervised learning algorithms used in the study: K-Nearest Neighbor (KNN), Convolutional Neural Networks (CNN), Random Forest, and Decision Trees. Each algorithm's processes and applications are explained, emphasizing their suitability for various tasks as shown in Fig. 1.

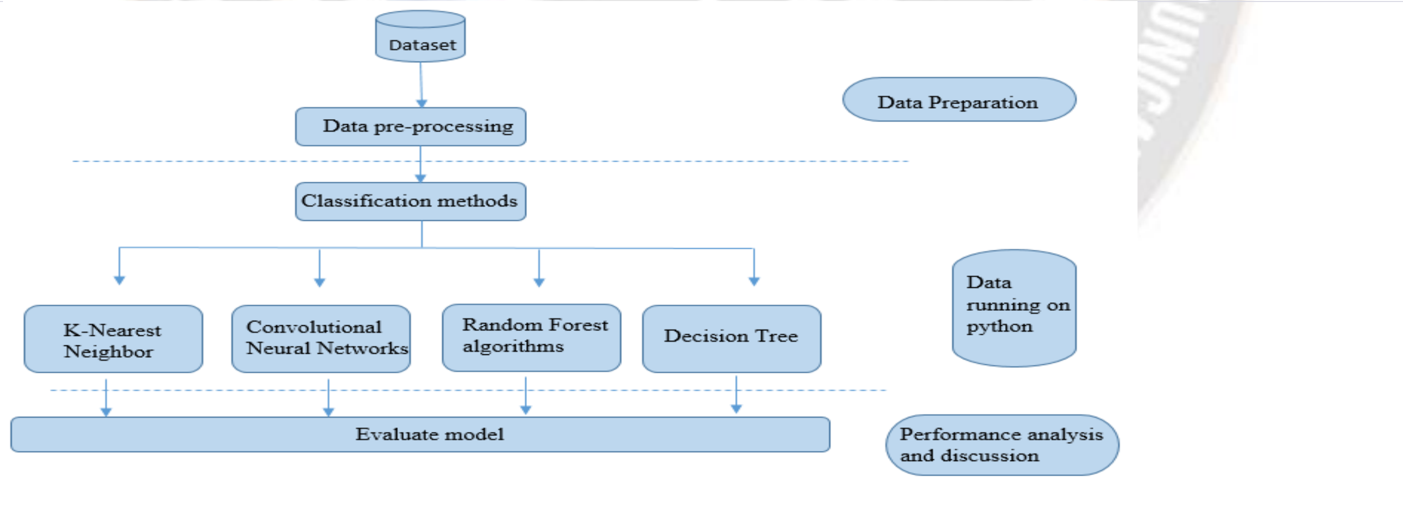

Figure 1: Design of the experiments

a) K-Nearest Neighbor Algorithm (KNN)

In our analysis, we applied the K-Nearest Neighbor (KNN) algorithm, a technique used for classifying entities based on their proximity to training samples in the problem space. KNN is a straightforward method: an item is assigned to the class most frequently chosen by its k closest neighbors (where k is typically a small positive integer), determined by a majority vote from those neighbors. If k equals 1, the object is simply placed in the category of its closest neighbor.

Here's a step-by-step explanation of how the KNN algorithm operates (Fauci, 2015):

- Calculate the Euclidean distance between the target point and the training data points.
- Retrieve samples while considering the computed distances.
- Select the best k nearest neighbors.
- Compute the weighted average of the inverse distances between the nearest k neighbors using multiple variables.

According to the fundamental concept of the algorithm, a query point (q_i) can be classified into a specific category if most of the K most similar samples in the feature space belong to that category. This method is referred to as the K-Nearest Neighbor algorithm because it measures similarity using distances in the feature space.

To determine the classification of a test point (qi), calculate the distances between it, represented by a vector in the feature space, and each point in the training data set. The class label of the test point (qi) is then determined by the labels of the k nearest points in the training data set after sorting the distance calculations.

Each point in the d-dimensional space can be represented using a d-vector for coordinates, as shown in Equation 1:

$$p = (p_{1,} p_{2,} \dots, p_n) \qquad (1)$$

There are various methods for computing the distance between two points in a multi-dimensional feature space, with the Euclidean distance, as shown in Equation 2, being the most used method:

$$dist(p, q) = \sqrt{\sum_{i=1}^{n} (p_i - q_i)^2} \qquad (2)$$

b) Convolutional Neural Networks Algorithm (CNN)

In our analysis, we employed the Convolutional Neural Network algorithm, often referred to as CNN. CNN is a deep learning algorithm that finds widespread application in tasks related to image recognition and processing. Below are the key steps in the training and utilization of the CNN algorithm as shown in Table 1.

Table 1: Steps for CNN algorithm

Step 1	Read data from the database for the experiment.
Step 2	Divide data into inputs and output variables.
Step 3	Performing a normalization process for the data to make it within a close scale to each other.
Step 4	Divide the experiment data into trained data and test data to obtain the required accuracy
Step 5	Design the CNN model and layers.
Step 6	Entering data into the system to train it, and then testing it.
Step 7	Measurement of the resulting resolution ratio of the model.

The fundamental concept underlying the Convolutional Neural Network (CNN) algorithm is to utilize convolution to autonomously acquire and extract significant features from input data, particularly for tasks associated with images or other grid-like structures.

CNNs draw inspiration from the arrangement of neurons in the visual cortex of animals, where each neuron is responsive to distinct regions of the visual field. Similarly, CNNs comprise layers of interconnected neurons that develop the ability to identify patterns and features at varying scales within an input image.

c) Random Forest Algorithm (RF)

In our analysis, we utilized the Random Forest algorithm, a supervised learning tool capable of handling both classification and regression tasks. This approach demonstrated superior performance compared to other machine learning techniques.

The term "random forest" refers to a classification method where each tree-based classifier "votes for the most prevalent category when given input x," and the "k" values are independent identically distributed random vectors (Pavlov, 2019). In essence, the random forest method constructs decision trees from random subsets of data, generates predictions from each tree, and then aggregates the results through a voting mechanism to select the most reliable prediction.

The key steps involved in the Random Forest algorithm are as follows: The data is initially divided into numerous random groups. For each sample, the algorithm constructs a decision tree. Subsequently, predictions from each decision tree are collected, and a majority vote is conducted to determine the final prediction.

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d) Decision Tree Algorithm (DT)

We applied this method to our student records dataset. The decision tree algorithm builds models using a top-down approach, which is a highly effective technique for supervised learning (Fig. 2).

One of the most well-known decision tree algorithms is ID3, which facilitates the creation of reasonably sized decision trees without extensive computational demands. ID3 exhibits several features and is particularly effective with large training datasets. It constructs a decision tree from a subset of the training group, chosen at random, and accurately classifies all the objects within this subset. This decision tree is then employed to classify the remaining objects in the training group. If the tree correctly classifies all objects, the training group has successfully learned, and the process concludes. However, if misclassifications occur, these objects are added to the subset, and the process iterates[12].

The ID3 algorithm initiates with the root node, represented by the initial set S. During each iteration of the algorithm, every unused feature of the S group is assessed to determine the feature's information gain IG(S) or entropy H(S). The feature with the lowest entropy—or the highest information gain—is selected. Subsequently, the S-group is split into subsets based on this chosen attribute. Within each subset, the algorithm recurs, selecting only features that have not been chosen before. Entropy H(S) is computed as shown in Equation 3 [1]:

$$H(s) = \sum_{x \in X} -p(X) \log_2 p(x) \tag{3}$$

The information gain IG(S) is calculated as shown in Equation 4 [1]:

$$IG(A, S) = H(S) - \sum_{t \in T} p(t)\, H(t) \tag{4}$$

Where:

S: The dataset being evaluated

X: Set of classes in S

p(x): The proportion of elements of class x in the dataset S

H(S): The entropy of dataset S

T: Subsets created by splitting dataset S based on attribute A

p(t): The proportion of elements of t in the dataset S

H(t): The entropy of dataset t

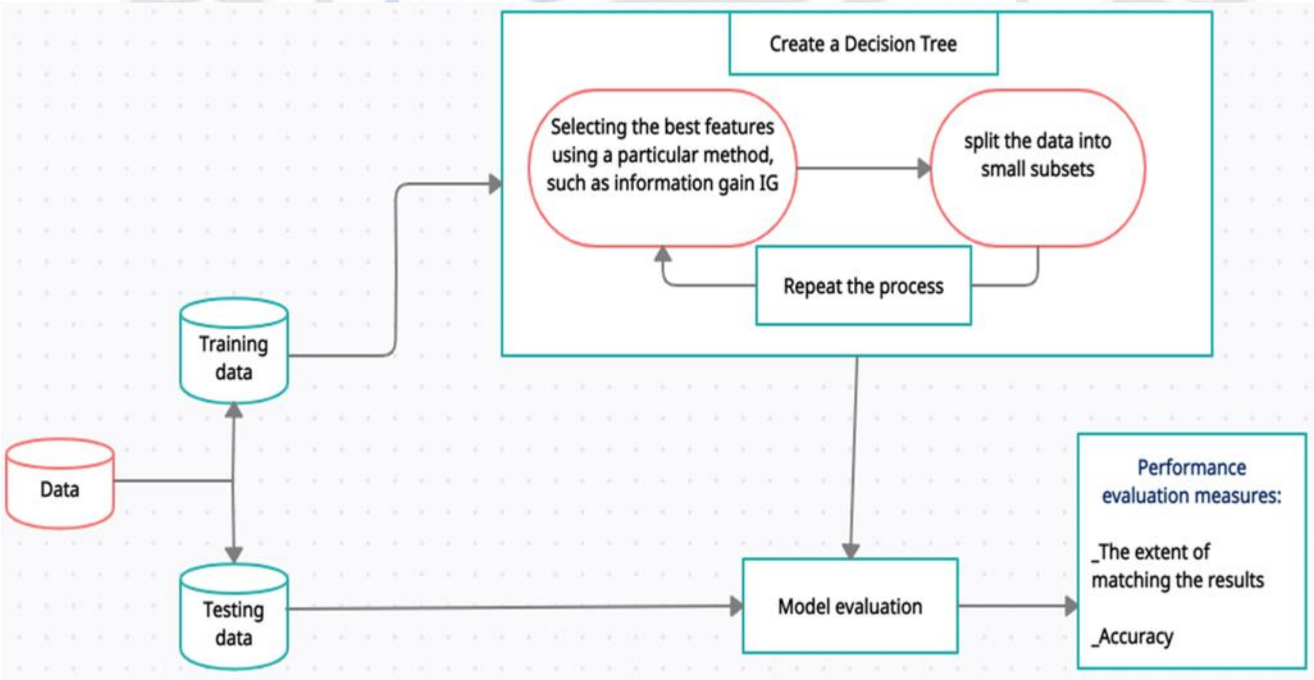

Figure 2: Decision Tree algorithm.

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e) Research Ethics

Ethical considerations are paramount in this study. Informed consent was obtained from participants, assuring them of confidentiality. Data confidentiality and anonymity measures were taken to protect participants' identities. Ethical considerations extended to the examination of online content, where public domain discussions were analyzed without compromising individual privacy. Additionally, the study acknowledges its ethical responsibility in utilizing predictive insights for decision-making affecting both online and offline communities.

IV. EXPERIMENT RESULTS AND ANALYSIS

1) Data Analysis

The data collected underwent comprehensive analysis using various methodologies to extract meaningful insights.

4.1.1 Sentiment Analysis: Data Analysis

Following the cleaning and preparation of raw data extracted from university Facebook groups, the dataset encompassed a total of 7,000 text messages. This volume of data allowed for the advantages associated with big data analysis, including size, speed, and diversity (McAfee et al., 2012). The dataset was rich in recent and varied information sources, comprising comments, posts, and responses from various contributors, making it ideal for sentiment analysis.

Sentiment analysis was conducted using Nvivo, a computer-assisted qualitative content analysis software (CAQCAS). Nvivo utilizes computational linguistics and text mining techniques to identify textual emotions, typically categorized as positive, neutral, or negative. Essentially, sentiment analysis serves as an automated method for uncovering hidden patterns within extensive datasets.

In sentiment analysis, a crucial step involves word classification, which can be accomplished through two general methods: the body-based method and the lexicon-based method (Miao, Li & Zeng, 2010). However, the body-based method is infrequently used in sentiment analysis. Both the body-based method and the lexicon-based method rely on predefined dictionaries or sets of subjective words. In this research, the relevant text was compared to a dictionary or lexicon to gauge the intensity and polarity of emotions.

Specifically, this study utilized the Nvivo page search engine for Windows to conduct sentiment and text analysis.

2) Keyword Analysis and Insights from Social Media Big Data: Data Analysis

Keyword analysis and related social media big data metrics, such as the total number of posts, comments, and likes, obtained from the opinions of students and faculty members on university decisions and legislation, were processed using Microsoft Excel. Facebook group content was broken down into individual words, and the frequency of each word was determined. Words were then ranked from most to least frequently used. Notably, the most frequently used words were often devoid of clear, independent meaning, and they were filtered to ensure practicality in the analysis.

3) Netnography: Data Analysis

The data collected via the Nvivo capture plug-in for the Google Chrome browser was analyzed by reviewing posts and their respective comments within the dataset. Text messages and accompanying images, where relevant, were examined. Initial data analysis involved coding messages by creating nodes. Any text, link, or image unrelated to the opinions of students and faculty members on university decisions and legislation was considered spam and disregarded, as it did not appear to be relevant to the project.

Upon establishing categories for both positive and negative sentiments expressed by students, faculty, and administrators, mind maps and word trees were created for further analysis.

4) Applied Ethics in Digital Humanities for Decision Distribution in Higher Education Questionnaire on Student and Faculty Opinions

This study conducted a questionnaire between May 3rd and May 10th, 2022, targeting a representative sample of students and professors at the University of Jordan. The sample aimed to represent the University of Jordan's student body with a margin of error not exceeding ± 4%.

The questionnaires covered various topics, and it was noted that some answers required further discussion, clarification, and conclusions.

a) Decision on Standardizing Semester Hour Limits for Bachelor’s Students

Fig. 3 summarizes students' awareness of the decision to standardize semester hours. Results show 44.2% well-informed, 37.7% moderately knowledgeable, and 18.2% with incomplete awareness. Overall, students demonstrate awareness of Ministry of Higher Education decisions.

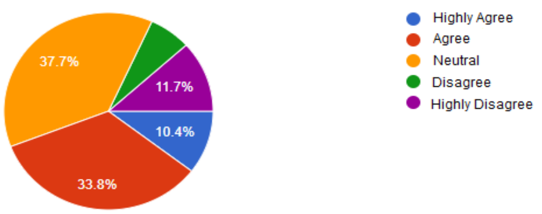

Figure 3: The extent of student's knowledge in the decision to standardize the upper limit of the semester hours.

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Fig. 4 indicates that 44.7% of surveyed students believed their higher education institution offered moderate clarity on the expected benefits of standardizing semester hours, while 39.4% felt the benefits were inadequately clarified. In Fig. 5, 45.5% of students disagreed with the idea that unifying the upper limit of semester hours had a positive impact.

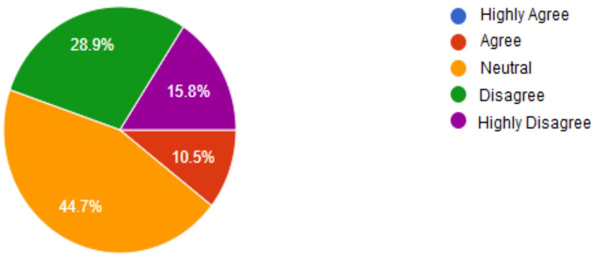

Figure 4: The institution of higher education has clarified the expected benefits of implementing the decision to standardize the upper limit of semester hours.

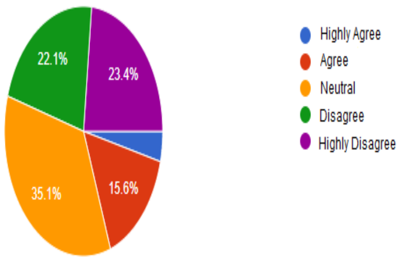

Figure 5: The decision to unify the upper limit of semester hours has a positive effect on academic achievement.

Regarding the time allocated for implementing the decision to standardize the upper limit of semester hours and students' satisfaction, Fig. 6 indicates that most students believe their higher education institution did not provide sufficient time. Fig. 7 further reveals that 62.4% of students express dissatisfaction with the decision.

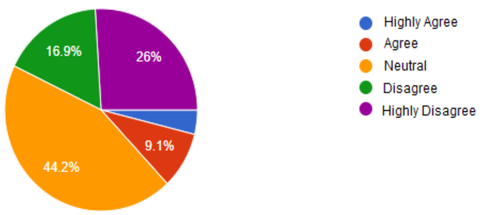

Figure 6: The institution of higher education works to give students sufficient time to implement the decision to standardize the upper limit of semester hours.

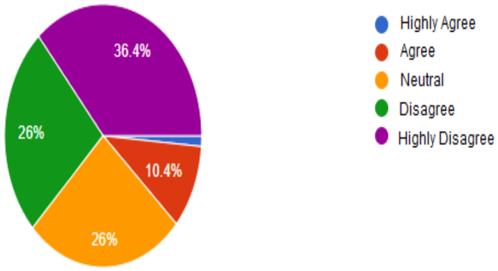

Figure 7: Students' satisfaction with the decision to standardize the upper limit of semester hours.

b) Used the scale system in evaluating students.

In Fig. 8, The student's knowledge of the scale system issued by the University of Jordan is good knowledge, with 50% voting that they know the scale system and 40% of students know the decision moderately. While 10% do not have complete knowledge of the decision.

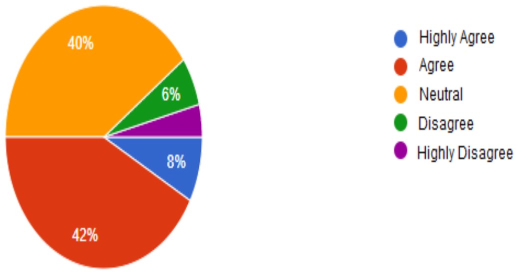

Figure 8: The extent of students' knowledge in the scale system issued by the University of Jordan.

As for the expected benefits of implementing the scale system, 44% voted that the students think that The University of Jordan has not clarified the expected benefits of implementing the scale system. It's shown in Fig. 9, But 40% of students think the scale system has a positive effect on academic achievement, Fig. 10 shows that 40% of the total number of students who participated in filling out the Questionnaire believed that the scale system did not achieve justice among students, as shown in Fig. 11, Fig. 12 illustrates that 66.7% of respondents moderately agreed with their satisfaction with the scale system.

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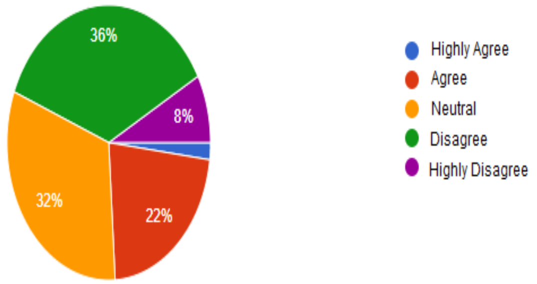

Figure 9: The University of Jordan has clarified the expected benefits of implementing the scale system.

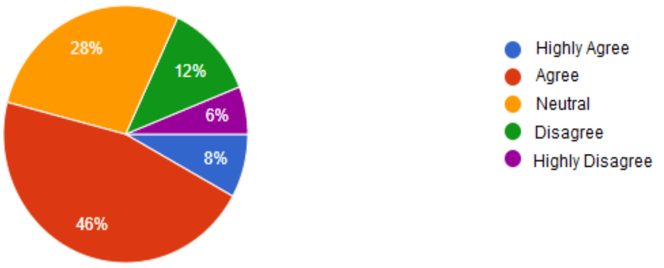

Figure 10: The scale system has a positive effect on academic achievement.

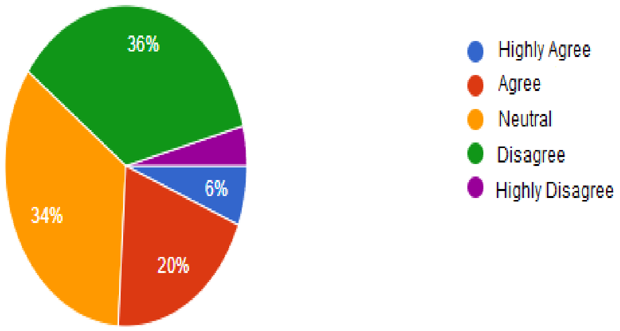

Figure 11: The scale system achieves justice among students and each student gets the mark he deserves.

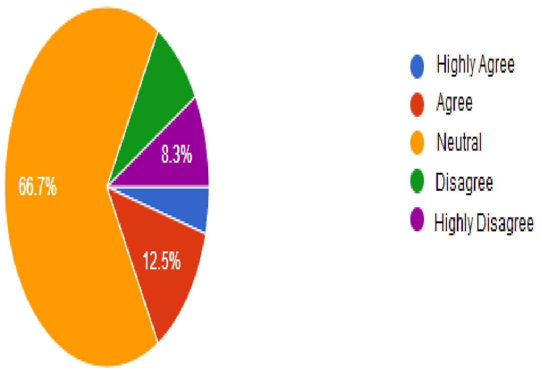

Figure 12: Students' satisfaction with the scale system

c) Decision Canceling the holding of the English language level exam in the language centres in the official Jordanian universities and limiting itself only to the English language exams that are held internationally.

Fig. 13 where students were asked about the extent of their knowledge in A decision to cancel the holding of the English language level exam in the language centres in the official Jordanian universities, and to limit itself to the English language exams that are held internationally. 46.7% of students know the decision well, and 25.4% of students know the decision moderately. While 27.9% do not have complete knowledge of the decision, which indicates students' awareness of following up on the decisions and legislation issued by the Ministry of the Higher Education Institution.

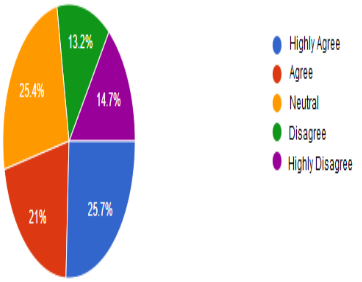

Figure 13: The extent of students' knowledge in the Decision to cancel the holding of the English language level exam in the language centres in the official Jordanian universities, and limiting itself only to the English language exams that are held internationally.

Fig. 14 reveals that 65.3% of surveyed students believed their higher education institution did not clarify the expected benefits of cancelling the English language level exam in language centers. Simultaneously, Fig. 15 shows that 79.6% felt there wasn't sufficient time for the decision's implementation. Consequently, Fig. 16 indicates that 76.7% of students voted expressing dissatisfaction with that decision.

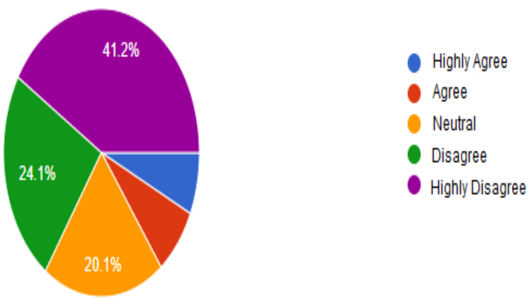

Figure 14: The institution of higher education has clarified the expected benefits of implementing the Decision to cancel the

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holding of the English language level exam in the language centres in the official Jordanian universities, and limiting itself only to the English language exams that are held internationally.

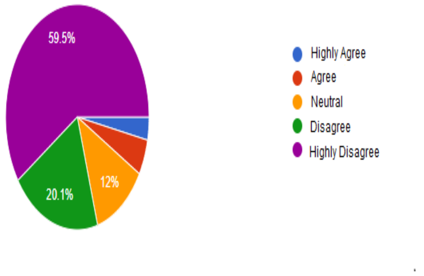

Figure 15: The institution of higher education works to give students sufficient time to implement the decision to cancel the holding of the English language level exam in the language centres in the official Jordanian universities and limit itself only to the English language exams that are held internationally.

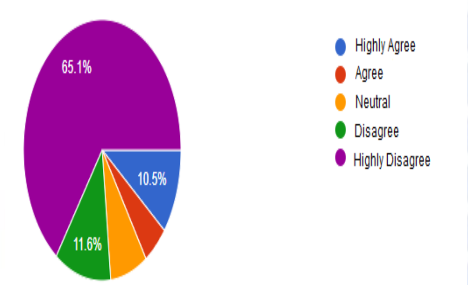

Figure 16: Students' satisfaction with the decision to cancel the holding of the English language level exam in the language centres in the official Jordanian universities, and limiting itself only to the English language exams that are held internationally. It's shown in Fig. 17, that 59% of students think the decision to cancel the holding of the English language level exam in the language centres in the official Jordanian universities has no positive effect on academic achievement.

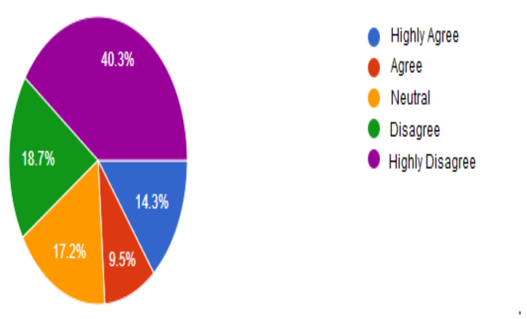

Figure 17: The Decision Canceling the holding of the English language level exam in the language centers in the official Jordanian universities and limiting itself only to the English language exams that are held internationally. Has a positive effect on academic achievement.

d) A decision to be studied by the Ministry of Higher Education and scientific research about supporting the university's relationship with students' parents.

In Fig. 18, 37.5% of students voted against the idea of supporting the university's relationship with students' parents. However, in contrast, 75% of students anticipated that this idea would be accepted by their parents, as indicated in Fig. 19. Furthermore, in Fig. 20, 58.3% of students voted in favor of the decision to support the university's relationship with parents, believing it would help parents get answers about their son's life and academic progress. This, according to 54.2% of respondents in Fig. 21, is expected to positively impact academic achievement.

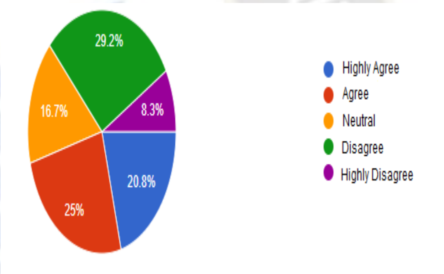

Figure 18: The extent to which students accept the idea of supporting the university's relationship with parents.

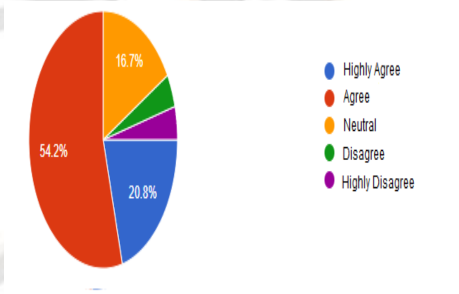

Figure 19: The idea of supporting the university's relationship with students' parents will receive interest from parents.

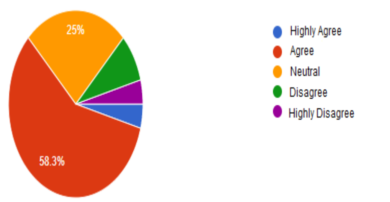

Figure 20: The decision to support the university's relationship with students' parents helps to positively influence educational attainment.

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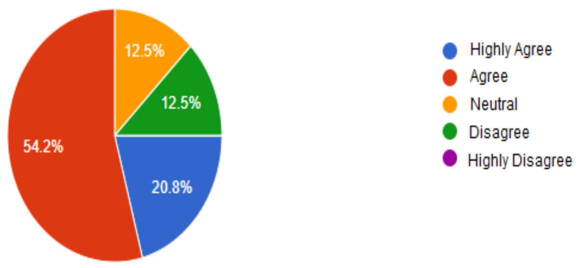

Figure 21: The decision to support the university's relationship with students' parents helps parents to get answers to their questions about their son’s life at the university and their academic level.

5) Evaluation of Data Analysis

In this section, we employed the NVivo tool to analyze the opinions of both students and faculty members concerning decisions and legislation issued by the University. Various methods were employed to gather data for analysis using NVivo [2]:

1. Online social media.
2. Online Questionnaires and Applications.

Initially, we organized the data into eight separate files for ease of reference, with each decision having two corresponding files:

1. The Questionnaire Results File.
2. The Online Social Media File.

Subsequently, we conducted an overarching analysis of the entire dataset without specific keyword searches, focusing instead on measuring the frequency of words across the document set.

The most frequently used words were identified by their size, with the largest representing the most common words and the smallest representing less frequent terms. Let's delve into the analysis of each set of files:

1. Analysis of Files (Decision to Standardize the Upper Limit for Semester Hours in All Universities and University Colleges for bachelor’s Students)

In Fig. 22, the five most frequently used words are "moderately," "knowledge," "time," "graduation," and "enough." Interestingly, the most prominent word appears to be a hashtag: "Moderately knowledgeable in the decision. Students expected to graduate disagree with the decision due to insufficient time to implement it."

Figure 22: Word Frequency.

2. Analysis of Files (Use of the Scale System in Evaluating Students)

Fig. 23 suggests that university students perceive the evaluation system as unfair but acknowledge its positive impact on academic achievement.

Figure 23: Word Frequency.

3. Analysis of Files (Decision to Cancel the Holding of the English Language Level Exam in Language Centers at Official Jordanian Universities, Limiting It to Internationally Held Exams)

Fig. 24 highlights the word "disagree" to a significant extent, indicating that students largely rejected this decision, likely due to its sudden implementation.

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Figure 24: Word Frequency.

4. Analysis of Files (Decision to Be Studied by the Ministry of Higher Education and Scientific Research Regarding Support for the University's Relationship with Students' Parents)

In Fig. 25, it is evident that most students agree with the decision, anticipating that it will be well-received by parents. They believe it will lead to improved educational outcomes and raise the overall educational standards.

Figure 25: Word Frequency.

6) *Experiment and Results*

In this segment, we present the outcomes derived from employing four distinct prediction algorithms (KNN, CNN, RF, and DT) to anticipate educational outcome quality based on questionnaire data. Fig. 26 illustrates the accuracy of these prediction algorithms across the four questionnaires. A key observation from this depiction is that KNN exhibits varied accuracy levels spanning from 75.67% to 94%. It excels particularly in discerning patterns within specific datasets, notably in Q3 and Q4. Conversely, CNN demonstrates a mixed performance, displaying accuracies ranging from 69.90% to 86%. While it performs admirably in Q4, it encounters challenges in Q2, indicating sensitivity to questionnaire nuances.

Meanwhile, Random Forest consistently emerges as a robust performer, attaining high accuracies across all questionnaires, ranging from 92% to 97%. The efficacy of its ensemble learning approach becomes apparent in effectively capturing diverse patterns. On the other hand, the Decision Tree yields reasonably accurate results, ranging from 78% to 85%. Despite not consistently securing the top position, its interpretability renders it valuable in scenarios where comprehending decision rules holds paramount importance.

Moreover, the performance of these algorithms fluctuates across different questionnaires, underscoring the significance of considering data nature and questionnaire characteristics in algorithm selection. Random Forest, exhibiting unwavering robustness, proves to be a dependable choice across a spectrum of datasets, owing to its ability to aggregate insights from multiple decision trees.

In conclusion, the choice of a prediction algorithm should be finely tuned to the specific attributes of the data and the objectives of the analysis. Random Forest emerges as a steadfast selection for consistent and robust performance. However, the decision to employ KNN, CNN, or Decision Tree hinges on the intricacies unique to each questionnaire and the broader contextual requirements of the analysis.

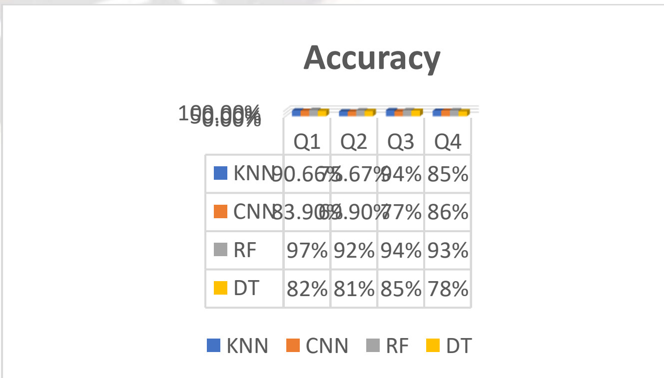

Figure 26: The accuracy of prediction algorithms among the four questionnaires.

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Table 2 and Fig. 27 show the performance matrix of the prediction algorithms among the four Questionnaires.

Analyzing Fig. 27 nd referring to Table 2, we can draw the following conclusions:

KNN consistently demonstrates precision and recall scores across all four quarters, reaching a notable peak in Q3 with the highest values for both metrics. The F1-Score remains relatively stable, indicating a balanced performance throughout the quarters.

CNN displays a performance that varies across quarters, with Q4 exhibiting the highest precision, recall, and F1-Score. Despite a slight dip in Q2, the algorithm showcases resilience by rebounding in subsequent quarters.

Random Forest performs strongly, particularly excelling in Q1 and Q4, where it attains the highest F1-Score. The precision and recall values exhibit a consistent level of stability across all quarters, showcasing the algorithm's predictive capabilities.

Decision Tree shows varying performance across quarters, with Q2 displaying the highest precision and Q3 demonstrating the highest recall. Despite fluctuations, the algorithm maintains a relatively stable F1-Score throughout the four quarters.

In summary, these findings offer insights into the performance of the algorithms across diverse evaluation metrics and periods. The observed variations underscore the significance of considering specific contexts and objectives when selecting a machine learning algorithm.

Table 2: The performance of prediction algorithms.

P. Alg.	Q1			Q2			Q3			Q4		
	Prec.	Recall	F1-SC	Prec.	Recall	F1-SC	Prec.	Recall	F1-SC	Prec.	Recall	F1-SC
KNN	0.93%	0.93%	0.93%	0.68%	0.70%	0.72%	0.99%	0.97%	0.95%	0.80%	0.82%	0.81%
CNN	0.83%	0.80%	0.81%	0.60%	0.68%	0.64%	0.75%	0.73%	0.77%	0.85%	0.82%	0.86%
RF	0.91%	0.92%	0.93%	0.79%	0.78%	0.81%	0.81%	0.87%	0.83%	0.90%	0.87%	0.93%
DT	0.81%	0.87%	0.83%	0.93%	0.87%	0.91%	0.83%	0.87%	0.91%	0.80%	0.78%	0.75%

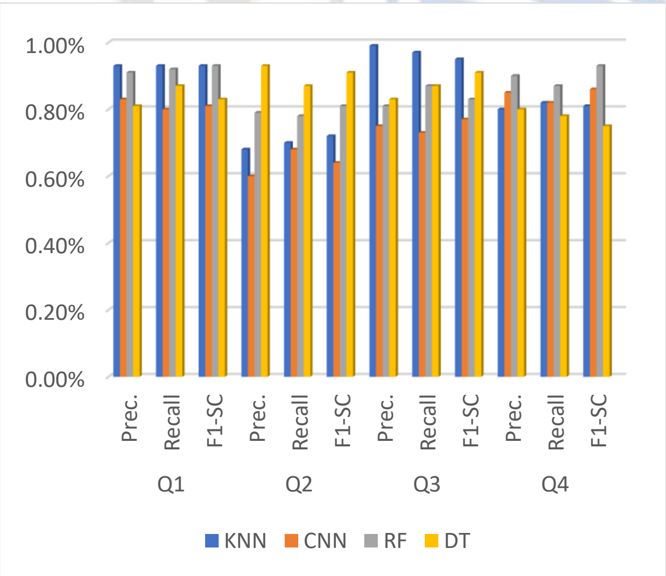

Figure 27: The effectiveness of prediction algorithms.

V. CONCLUSION AND PROSPECTS

Universities are dedicated to enhancing educational outcomes, which hinge on various factors including students' contentment with the directives and regulations established by higher education institutions. To delve into this, our scholarly endeavour delved into students' perspectives concerning these educational decrees. Commencing with data collection via an electronic questionnaire disseminated among University of Jordan students, we employed a Netnography mixed method research design with rigorous ethical considerations. Central to this was the meticulous application of the Netnography methodology. Examination of the amassed data revealed that student satisfaction with these decisions is contingent upon multiple facets, encompassing comprehension of the decision, its benefits, impact, and implementation timeline. This scrutiny was extended to four distinct higher education decisions and regulations.

Furthermore, we harnessed four machine learning algorithms namely, K-Nearest Neighbors (KNN), Convolutional Neural Network (CNN), Random Forest (RF), and Decision Tree (DT) to dissect the higher education institutional decisions.

Initially, these four algorithms were employed to assess specific decisions issued by the Ministry of Higher Education and Scientific Research. Notably, the Random Forest (RF) algorithm displayed the most remarkable performance, achieving an accuracy rate of 97% in the initial questionnaire. This slightly diminished to 92% in the second questionnaire due to the expanded dataset and various factors influencing accuracy. Subsequently, the K-Nearest Neighbors (KNN) algorithm yielded impressive outcomes, achieving an exceptional 94% accuracy in the third questionnaire.

These accuracy rates furnish invaluable insights into the efficacy of each algorithm in addressing distinct higher education decisions. Nevertheless, it remains imperative to consider the broader context, methodology, and dataset of the study to comprehensively decipher the outcomes and derive meaningful conclusions.

This research encapsulates the perspectives of University of Jordan students about decisions and legislation enacted by the Ministry of Higher Education and Scientific Research. In forthcoming research, we aspire to broaden the scope by encompassing student data from diverse universities and examining faculty members' viewpoints on the same decisions and regulations. Additionally, we intend to employ alternative algorithms to predict the quality of educational outcomes. While our study utilized Netnography via Facebook data, we envisage extending this approach to encompass data extracted from Twitter. This expansion could enable researchers to delve into emotions such as happiness or sadness experienced in response to decisions and regulations promulgated by the Ministry of Higher Education and Scientific Research.

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