Enhancing educational environments with Social Media Feedback Evaluation Employing Hybrid Neutrosophic Decision Optimization (HNDO) and Neutrosophic Sentiment Fusion (NSF)

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Abstract

This research work examines the critical challenge of enhancing educational environments through social media feedback, often impeded by the very uncertainties and complexities offered by textual data. Existing approaches either may indulge in sentiment analysis or may take the approach of basic data mining; nevertheless, they seldom consider ambiguity, contextual subtlety, and dynamic interventions. We propose an entirely new framework using Hybrid Neutrosophic Decision Optimization (HNDO) and Neutrosophic Sentiment Fusion (NSF) with deep learning-for advanced feature extraction-and reinforcement learning-for adaptive intervention strategies, with Explainable AI (XAI) for transparency. Presenting a new Neutrosophic Quantum Squirrel-Whale Decision Optimization (NQSWDO) framework to optimize educational enhancements based on feedback surveys and social media sentiment analysis, where it can collect, preprocess, extract features, fuse sentiments, optimize decisions, and detect concerns through reinforcement learning before interpreting feedbacks. A Neutrosophic Sentiment Fusion (NSF) model is applied to bring improvement into the accuracy of sentiment classification. Further refinement of educational improvements will come through the new application of hybrid neutrosophic decision optimization (HNDO), which incorporates multi-criteria decision analysis (MCDA) and fuzzy logic. For identification of key concerns, the VGG-Darknet detection model will be used, as well as a deep Q-network (DQN)-based reinforcement-learning system that dynamically intervenes in topic analysis. The last phase will comprehensively interpret feedback and adopt decision-making strategies to avoid wasting time in properly formulating useful educational policies. The results from the experiments indicate the practicality of the proposed framework for improving education decision-making through advanced methodologies on sentiment analysis, optimization, and reinforcement learning.

Keywords - Neutrosophic Logic; Educational Environments; Social Media Feedback; Hybrid Neutrosophic Decision Optimization (HNDO); Neutrosophic Sentiment Fusion (NSF); Quantum Optimization Algorithms; VGG-Darknet Detection Model; Explainable AI

1. Introduction

Educational environments have undergone significant transformation because of digital technology integration especially since educational systems transitioned to remote and hybrid learning models globally [1][2]. Social media functions as an essential connection between educational stakeholders because students, educators, and administrators now use it to communicate feedback and share learning experiences about teaching methods and curriculum development together with institutional policies [3]. The qualitative nature of received feedback generates valuable information, which can guide improvements for learning outcomes while enhancing student engagement and helping institutions become more adaptable. The conventional analytical methods struggle to

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handle the unstructured massive dynamic nature of social media data because these methods cannot properly address the uncertainties and ambiguities and contradictions found within such datasets [4][5].

The standard methods of sentiment analysis and decision-making through statistical models and basic machine learning techniques create simplistic decisions by reducing human feedback to binary categories [6][7]. These analysis methods fall short when it comes to interpreting social media content because they do not recognize the neutrosophic nature of opinions which contain truth values alongside indeterminacy and falsity components [8][9]. A student feedback comment might include truthful statements about content delivery but also mixed feelings about assessment fairness and false statements about technical support. The complex nature of social media content requires an analytical system which effectively combines various states to produce meaningful results [10][11][12].

This research develops an innovative framework which unites Hybrid Neutrosophic Decision Optimization (HNDO) with Neutrosophic Sentiment Fusion (NSF) to bridge the existing gap [13][14]. The framework uses neutrosophic logic to expand fuzzy and intuitionistic sets by adding indeterminacy as a separate dimension while HNDO combines various decision-making approaches to enhance ambiguous feedback interpretation [15]. The NSF uses neutrosophic sets to combine sentiment data collected from various social media platforms which results in an all-encompassing emotional analysis of stakeholder sentiments. The combination of these methods provides educators and policymakers with an effective system to interpret intricate feedback patterns so they can make informed adaptive choices.

The research work's major contribution is:

- Introduces explanation of the newly developed Neutrosophic Quantum Squirrel-Whale Decision Optimization (NQSWDO) framework in making decisions in education from social media feedback.
- Promulgates the Neutrosophic Sentiment Fusion (NSF) model to increase classification accuracy in sentiment analysis among which one is inconsistency.
- The hybrid Neutrosophic Decision Optimization (HNDO) framework is deployed that integrates Multi-Criteria Decision Analysis (MCDA) and fuzzy logic to furnish an optimum solution for educational improvements.
- VGG-Darknet for concern topic detection so the critical extraction of topics in the education landscape is done more accurately.
- Includes Deep Q-Network (DQN)-based reinforcement learning to dynamically intervene in discussions on emerging topics to enhance adaptability.
- The study focuses on Explainable AI (XAI) techniques such as LIME and SHAP, thereby lending transparency and trust to its decision-making, which becomes vital in its practical applications to educational environments.

The rest of the paper is organized as follows: Section 2 discusses the existing works related to the proposed subject. Section 3 provides a brief overview of the proposed approach. Section 4 details the results of the proposed project against some evaluation metrics based on existing approaches. The paper concludes in section

2. Related work

In 2023, Alnaqbi and Fouda [16] presented ChatGPT and social media as tools to collect immediate student assessments regarding teaching approaches in higher education settings. Neutrosophic sets serve as the framework to process uncertain and ambiguous information in student evaluation data. This method establishes a more efficient method of teaching style evaluation that outperforms traditional paper-based surveys.

In 2021, Awajan et al. [17] developed a new approach, which combines NS theory with Sentiment analysis (SA), and multi-attribute decision-making (MADM) techniques to create rankings of products based on online review data. The paper presents Neutro-VADER (Valence Aware Dictionary and sEntiment Reasoner) which represents an advanced sentiment analysis system that delivers truth, indeterminacy and falsity scores through neutrosophic analysis. The method employs the simplified neutrosophic number weighted averaging (SNNWA) operator together with cosine similarity measure for alternative ranking through a system that enhances uncertainty management. An analysis using Twitter data confirms the effectiveness of the proposed method that outperforms PROMETHEE II, TOPSIS, and TODIM in ranking products based on online reviews.

In 2023, Ahmadi et al. [18] presented a method for analysing Massive Online Open Courses (MOOC) platform user feedback to discover and rank user satisfaction influencing elements. The research implements sentiment analysis and topic modelling techniques on user feedback from popular courses before using DEMATEL analysis and network analysis to establish factor rankings and priorities. The optimization process for MOOC platforms requires analysis of course performance and identification of essential satisfaction factors to establish improvement priorities that will boost user satisfaction and completion rates.

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In 2025, Shi [19] suggested the Single-Valued Neutrosophic Number VIKOR (SVNN-VIKOR) approach to solve multi-attribute group decision-making (MAGDM) issues in measuring the satisfaction of college students with online ideological and political education (IAPE) under big data. It applies single-valued neutrosophic sets (SVNSs) to express uncertain information and data mining and analysis methods to gather feedback via online questionnaires and social media interactions. A numerical case study is presented to verify the validity of the proposed approach to enhance the precision of satisfaction estimation.

In 2021, Zou et al. [20] developed an automated text classifier, which uses modern machine learning approaches to extract social presence indicators from forum posts within MOOCs. The research investigates how social presence affects learner prestige by analysing social network analysis metrics such as in-degree and authority score. The study reveals particular social presence indicators that affect learner prestige in positive or negative ways, which helps, understand social presence enhancement strategies for online education social learning.

In 2025, Yasser et al. [21] introduced a neutrosophic framework with "truth," "falsity," and "indeterminacy" values serves as the basis to handle educational administration uncertainties. The research examines how cloud-computing tools specifically designed for data storage and analytics and collaborative functions allow administrators to control uncertainties. The research examines concrete case studies to prove how cloud-computing systems lower decision-making uncertainties. The research shows cloud-computing works effectively but its performance improves significantly when neutrosophic logic handles the natural indeterminacy in educational information.

In 2023, Kaleem et al. [22] suggested framework uses sentiment analysis in machine learning (ML) to evaluate student opinions about institutional library spaces. The system employs Natural Language Processing (NLP) alongside machine learning approaches to assign student feedback into positive, negative, or neutral categories. The research team conducted surveys while using Kaggle.com secondary data to conduct experiments. The sentiment analysis used Naive Bayes Multinomial and Support Vector Machine (SVM) algorithms to perform the analysis while F1-score calculations evaluated the system performance. The research generates valuable findings about student satisfaction toward library resources and services, which helps facilities management, evaluate and enhance their performance.

In 2022, Petronio and Sandro [23] introduced Amadeus-SIMM as a support system that enables teaching presence within computer-supported collaborative learning (CSCL) environments to boost social presence in online courses. The research examines if Amadeus-SIMM facilitates social interaction within collaborative learning environments. The effectiveness of the Python Programming distance course experiment was confirmed through survey data and system-generated reports and statistical analysis, which demonstrated improved social behavior visibility and engagement and information intermediation and learner prestige.

Moreover, the review on the existing works are mentioned in Table 1.

Table 1: Review on the State-of-Art approaches

Authors, Year	**Techniques**	**Significances**	**Limitations**
Alnaqbi and Fouda, 2023	ChatGPT, social media, Neutrosophic Sets	Enhances student feedback collection by addressing ambiguity in data	Ethical and practical concerns in using chatbots and social media for student evaluation
Awajan et al, 2021	Sentiment Analysis (SA), Neutrosophic Set (NS) Theory, Multi-Attribute Decision Making (MADM), Neutro-VADER, SNNWA, Cosine Similarity	Improves product ranking using sentiment analysis with better handling of neutral and uncertain data	Computational complexity of neutrosophic-based ranking methods
Ahmadi et al, 2023	Sentiment Analysis, Topic Modeling, DEMATEL, Network Analysis	Identifies and prioritizes factors affecting MOOC user satisfaction	Limited generalizability due to dataset dependency

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Shi, 2025	VIKOR, Single-Valued Neutrosophic Sets (SVNSs), MAGDM	Improves evaluation of student satisfaction in online ideological and political education	Dependence on data collection methods and survey quality
Zou et al, 2021	Automated Text Classification, Social Network Analysis (SNA)	Highlights the role of social presence in MOOCs and its impact on learner prestige	Not capture all dimensions of social presence
Yasser et al, 2025	Cloud Computing, Neutrosophic Framework	Addresses uncertainties in educational data for improved decision-making	Challenges in implementation and integration with existing educational systems
Kaleem et al, 2023	Sentiment Analysis, Natural Language Processing (NLP), Machine Learning (Naïve Bayes, SVM)	Evaluates student satisfaction with institutional facilities	Dataset limitation to a specific institution
Petronio and Sandro, 2022	CSCL, Amadeus-SIMM, Statistical Models (Chi-square, Difference of Means)	Supports teaching presence and improves social presence in online learning	Requires further validation across diverse online courses

3. Proposed Methodology

3.1 Overview

The aim of this study is to revolutionize how schools use student feedback by designing an exhaustive model that encompasses Neutrosophic Sentiment Fusion (NSF), Hybrid Neutrosophic Decision Optimization (HNDO), deep learning, reinforcement learning, and Explainable AI (XAI). Firstly, the data are collected for standard social media platforms and educational surveys to give an extensive and representative dataset. The next phase in preprocessing involves aspects such as tokenization, stop word removal; stemming, lemmatization, and handling of emojis that can help refine the textual data. Using feature extraction approaches such as Term Frequency-Inverse Document Frequency (TF-IDF), sentiment feature extraction, and Latent Semantic Analysis (LSA), meaningful insights can be induced from the processed text. The next step applies the Neutrosophic Sentiment Fusion (NSF), which improves the accuracy of sentiment classification in the presence of uncertainties in sentiment analysis. The introduction of the Hybrid Neutrosophic Decision Optimization (HNDO) model enables multi-criteria decision analysis (MCDA) with fuzzy to optimize educational decisions. It is further made accurate by the Neutrosophic Quantum Squirrel-Whale Decision Optimization (NQSWDO) method, which improves the optimization techniques in decision-making. These concerns are further identified in the educational perspective by using the VGG-Darknet detection model that would help in precise extraction of important discussion topics. By using reinforcement Learning, notably Deep Q-Network (DQN), topic discussions are dynamically intervened in by real-time adaptability. The last phase consists of feedback analyses, interpretations, and strategic decisions, which culminate in actionable policy recommendations for educational improvements. It is comprehensive with respect to the methodology in a data-driven approach to optimizing education systems based on social media feedback and survey analysis. The architecture of the proposed model is shown in Fig.1.

3.1 Phase 1: Data collection

Database 1: Student ratings and feedback for classes, instructors, and educational experiences in general can be accessed through the Student Feedback Dataset on Kaggle (https://www.kaggle.com/datasets/brarajit18/student-feedback-dataset). It includes several characteristics such as course ratings, textual feedback, sentiment labeling, and student demographics. It can be used for opinion mining, sentiment analysis, and assessing education quality. Student satisfaction, improving teaching styles, and streamlining course material are all possible uses of it. Scholars to explore patterns and nuggets within the feedback can utilize NLP and machine learning methodologies.

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Database 2: Student feedback and faculty staff ratings are part of the Sentiment Analysis of Faculty Evaluation Dataset on Kaggle (https://www.kaggle.com/c/sentiment-analysis-faculty-evaluation/data), which tries to classify sentiment as positive, neutral, and negative. To support natural language processing (NLP) tasks, it has sentiment labeling, text-based comments, and relevant information. This dataset can be useful for educational research, faculty performance assessment, and sentiment analysis. Researchers to train machine-learning models for opinion mining and feedback classification can utilize it. It assists in gaining a better understanding of the perceptions of the students and improves the quality of teaching.

3.2 Phase 2-Data Pre-processing

Pre-processing is where crucial data refinement takes place, including operations—exemplified by tokenization, stopping, stemming, lemmatization, and emoji handling—that enhance text standardization vis-a-vis feature extraction quality and reliability in the following phases.

3.2.1 Data Cleaning

Raw textual data includes various types of noise through irrelevant characters along with URLs and special symbols and misspelled words. The following operations make up data cleaning procedures.

- **Removal of Irrelevant Components**: URLs, HTML tags, numerical values, and special characters are eliminated using Eq. (1):

$$T' = f_{clean}(T) = T - \{URLs, HTML\ tags, special\ symbols, numbers\} \quad (1)$$

- **Spelling Correction and Abbreviation Expansion**: The system compares word w to dictionary D to replace incorrect spellings or abbreviations using Eq. (2):

$$T'' = \sum_{\omega \in W} f_{spell}(\omega),$$

where, $f_{spell}(\omega) \in D$ (2)

- **Duplicate Removal**: The identification and removal of duplicate posts and comments occurs through text hashing analysis of content or clustering methods for similar entry grouping as Eq. (3). The removal of repetitive data through analysis techniques protects the accuracy of sentiment analysis results.

$$D_{unique} = Unique(D_{original}) \quad (3)$$

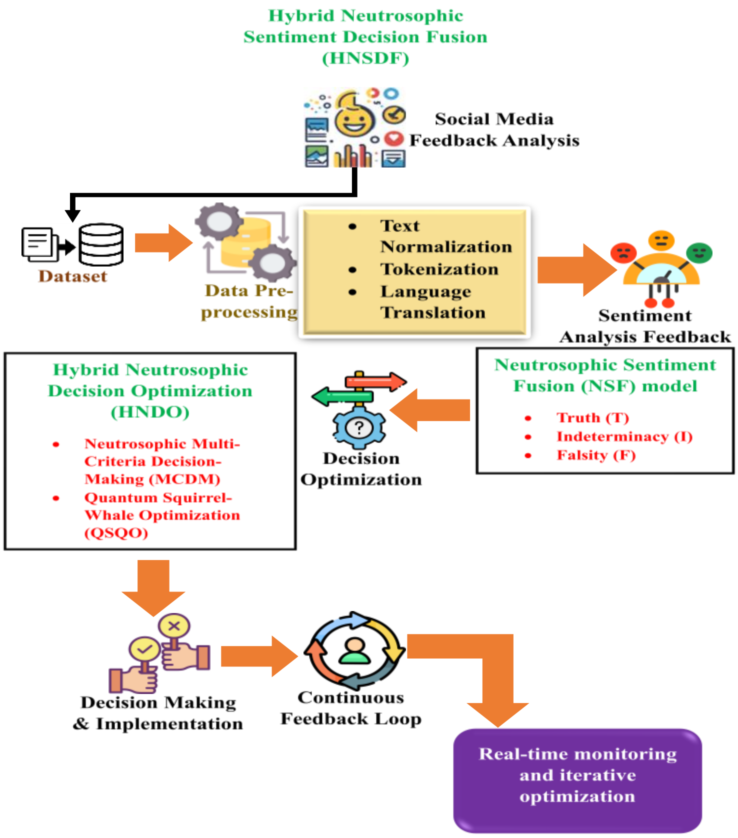

Figure 1. Architecture of the proposed model HNSDF

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3.2.2 Tokenization

The process of text segmentation into words or significant parts serves to make analysis possible. An input text T'' serves as the base for the tokenization function definition as Eq. (4):

$$T_{tokens} = f_{tokens}(T'') \tag{4}$$

3.2.3 Stop Word Removal

Commonly occurring words that do not contribute to sentiment ("the," "is," "and") are removed. The filtered text is obtained as Eq. (5):

$$T_{filterd} = T_{tokens} - S \tag{5}$$

Where, S represents the set of predefined stop words.

3.2.4 Stemming and Lemmatization

The normalization process through these techniques converts words into their fundamental root components:

- The heuristic rules of **stemming** remove suffixes from words, given by Eq. (6):

$$w_{stemmed} = f_{stem}(w) \tag{6}$$

- The dictionary-based method of **lemmatization** enables users to find appropriate base forms as Eq. (7):

$$w_{lemma} = f_{lemma}(w, POS) \tag{7}$$

3.2.5 Handling Emojis and Emoticons

The interpretation of emoticons and emojis requires conversion to text-based sentiment values or textual representations. The textual form of emoji e is established as Eq. (8):

$$e_{text} = f_{emoji}(e) \tag{8}$$

A sentiment lookup table L_{emoji} assigns a sentiment score as Eq. (9):

$$S_{emoji} = L_{emoji}(e) \tag{9}$$

3.3 Phase 3: Feature extraction

Techniques of feature extraction include TF-IDF feature extraction, sentimenal feature extraction, and LSA. It helps in extracting meaningful insights from processed text, which helps in proper estimation of opinions and concerns in the dataset accordingly. The following techniques are used for extracting the required features, and the techniques include Term Frequency-Inverse Document Frequency (TF-IDF), Sentiment Features, Topic Modeming LSA, and User Engagement Metrics respectively.

3.3.1 TF-IDF (Term Frequency-Inverse Document Frequency)

The relevance of a word within a document is quantified based on its TF-IDF, which contrasts its occurrence across the corpus. It helps in finding important words that differentiate documents. Moreover, it can be mathematically verified using the following Eq. (10),

$$TF - IDF(T, D) = TF(T, D) \times IDF(T) \tag{10}$$

Where, the parameter Tdefines the frequency and D representing the total number of data **3.3.2 Sentiment Features**

By considering truth, falsity, and indeterminacy, this approach measures sentiment and detects ambiguity in opinions. Moreover, it can be mathematically verified using the following Eq. (11)-(13),

$$Polarity = T - F \tag{11}$$

$$Uncertainity = I \tag{12}$$

$$Intensity = |T - F| \tag{13}$$

Here, the following parameters, $T$and F defining the true as well as the false scores, and I is the indeterminacy score.

3.3.3 Topic Modelling Latent Semantic Analysis (LSA)

By using Singular Value Decomposition (SVD) to decompose the document-term matrix, LSA reveals latent topics in the text, making topic discovery possible. Moreover, it can be mathematically verified using the following Eq. (14),

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$$d^* = U\Sigma v^t \tag{14}$$

Here, $d^*$is the document-term matrix, U is the topic distribution matrix, Σ defining the diagonal matrix of singular values and the following parameter v^tshows the distribution matrix

3.3.4 User Engagement Metrics

As measures of levels of engagement, the metrics count actions by social media users like sharing, commenting, and liking. Moreover, it can be mathematically verified using the following Eq. (15),

$$Encagementscore = W_1 \times Likes + W_2 \times Shares + W_3 \times comments \tag{15}$$

Here, the weights can be mentioned as W_1, W_2 and W_3respectively.

3.4 Phase 4: Neutrosophic Sentiment Fusion (NSF) model-based feature Extraction

To refine the sentiment classification capabilities, Neutrosophic Sentiment Fusion (NSF) is effectively incorporated. Through uncertainty handling in sentiment analysis, this model allows for comprehensive interpretation of subjective opinions across feedback data features (acquired from feature extraction stage). The sentiment expressed in the feedback is analysed using the NSF model. The NSF model is developed to deal efficiently with the indistinctness, contradiction, and uncertainty often present in social media content, which makes its treatment very difficult using the traditional method of sentiment analysis. The proposed architecture of the NSF model is structured in the Figure 2.

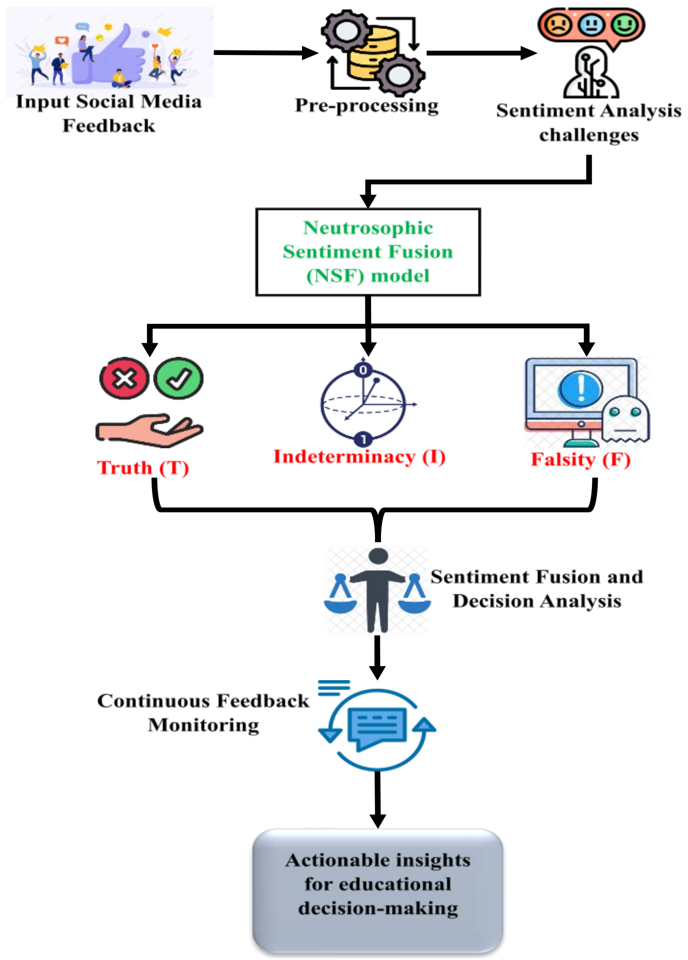

Figure 2. Architecture of the proposed NSF model

3.4.1 Challenges in Sentiment Analysis

Social media feedback is made up of heterogeneous and sometimes opposing opinions based on different factors like subjective interpretation, sarcasm, mixed emotions, and cultural context. Traditional sentiment analysis models normally label sentiments into binary or ternary categories (positive, negative, neutral), but they do not capture the subtlety of uncertain or ambiguous opinions. NSF addresses this drawback by utilizing neutrosophic logic that by considering the different degrees of truthfulness, indeterminacy, and falsity in sentiment.

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3.4.2 Core Components of NSF model

The NSF model stems from neutrosophic sets, which consider, in particular, three components for the analysis of sentiment.

a) Truth (T)

This comprises the degree of truthfulness or reliability in the sentiment expressed. A high truth-value indicates strong confidence that the sentiment is accurate and aligns with the given context. In mathematical terms, describing the degree of truthfulness (T) or reliability in sentiment analysis, sentiment confidence and context alignment-based truthfulness is stated in equation (22):

$$T_s = \frac{SC_s \times CA_s}{SC_s + CA_s + \epsilon} \tag{22}$$

Where, T_s is the degree of truthfulness of sentiment s. SC_s is the sentiment confidence score (probability of the sentiment label being correct). CA_s is the contextual alignment score (degree of how the sentiment is consistent with contextual indicators). ϵ is the small constant to avoid division by zero. Truthfulness Combining Sentiment Polarity and User Engagement as per the equation (23):

$$T_s = \alpha \cdot P_s + \beta \cdot \left(\frac{E_s}{E_{max}}\right) \tag{23}$$

Where, T_s is the degree of truthfulness of sentiment, P_s is the sentiment polarity strength (absolute value of polarity). E_s is the user engagement score (likes, shares, and comments). E_{max} is the maximum engagement in the dataset (for normalization). α, β are the weighting parameters controlling the influence of polarity and engagement. This formula equalizes polarity strength and influence on engagement in arriving at the truth value of an emotion.

b) Indeterminacy (I)

These inquiries into the degree of uncertainty in a piece of feedback. This description often applies to vague expressions, conflicting opinions, or unclear statements whereby the sentiment is not definitely identified as positive or negative. To numerically define the level of uncertainty (I) in a piece of feedback, the Uncertainty Based on Sentiment Variability and Conflict is presented in equation (24):

$$I_s = \frac{V_s + C_s}{V_s + C_s + D_s + \epsilon} \tag{24}$$

Where, I_s is the degree of uncertainty in sentiment s. V_s is the sentiment variability (difference in sentiment scores from different sources or methods). C_s is the conflict score (extent to which opposing sentiment labels are applied to the same text). D_s is the confidence level in sentiment analysis. ϵ is the very small constant to avoid division by zero. Yet, Uncertainty Based on Lexical Ambiguity and Engagement Dispersion is expressed in the equation (25):

$$I_s = \gamma \cdot \left(\frac{A_s}{A_{max}}\right) + \delta \cdot \left(\frac{1}{1+E_s}\right) \tag{25}$$

Where, I_s is the degree of uncertainty in sentiment s. A_s is the lexical ambiguity score (number of vague or neutral words). A_{max} is the maximum lexical ambiguity in the dataset (for normalization). E_s is the user engagement score (likes, shares, comments—higher engagement suggests greater clarity). γ, δ are the weighting factors to compensate for ambiguity and engagement. This formula captures the fact that increased ambiguity raises uncertainty, and greater engagement lowers it, since clearer sentiments get more user interactions.

c) Falsity (F)

It represents a degree of falsehood or negativity concerning the sentiment expressed. A high falsity value suggests that the feedback is essentially negative or misrepresentative or those inflatable arguments were employed in making it. To quantify the degree of falsity (F) in an expression of sentiment, the Falsity Based on Sentiment Polarity and Misrepresentation is given in equation (26):

$$F_s = \frac{N_s + M_s}{N_s + M_s + T_s + \epsilon} \tag{26}$$

Where, F_s is the degree of falsity in sentiment s. N_s is the negative sentiment polarity score (increasing negativity enhances falsity). M_s is the misrepresentation score (extent of exaggeration, sarcasm, or misleadingness). T_s is the truthfulness score (increasing truthfulness decreases falsity). ϵ is the tiny constant to avoid division by zero. Besides, Falsity Based on Sentiment Contrast and Inflated Arguments is shown in the equation (27):

$$F_s = \lambda \cdot \left(\frac{C_s}{C_{max}}\right) + \mu \cdot \left(\frac{IA_s}{IA_{max}}\right) \tag{27}$$

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Where, F_s is the degree of falsity in sentiment s. C_s is the sentiment contrast (difference between original sentiment and corrected/corrected sentiment). C_{max} is the maximum sentiment contrast in the dataset (used for normalization). IA_s is the inflated argument score (availability of overhyped claims or emotionally evocative words). IA_{max} is the maximum inflated argument score in the dataset. λ, μ are the weighting factors that govern the influence of contrast and exaggeration. This formula takes into consideration contradictions and exaggerated arguments as major contributors to falsity in expressions of sentiment.

Truth (T), Indeterminacy (I), and Falsity (F) are quantified numerically in a range between [0,1] and immediately enable one to assign the most precise measure of any sentiment, infinitely exceeding previous analyses of what actually makes or breaks the initiated sentiments.

3.4.3 Significance of NSF model

- **Increased Accuracy:** By putting modelling of uncertainty and inconsistency into their works, NSF achieves greater precision in sentiment analysis-based assessments than traditional approaches.
- **Robustness to Ambiguity:** Uncertain, sarcastic, or contradictory feedback is well understood by NSF, given that it is widely encountered in discussions on social media platforms.
- **Profound Sentiment Representation:** Instead of rigid classifications, NSF gives a more holistic and better picture of the sentiment by displaying truth, indeterminacy, and falsehood in a continuum.
- **Better Decision:** These improved sentiments allow educational institutions to make decisions relative to betterment in course content, improving ways of engaging students, and modernizing school rules.

The NSF model provides a sophisticated way of handling complex and uncertain sentiments in social media input. By applying neutrosophic logic, NSF accomplishes the processing and fusion of various sources of sentiments, thus ensuring a holistic and credible understanding of public opinion surrounding the educational arena. This model is particularly useful for decision-makers who must tackle the intricacies of different, often conflicting feedback in an educational setting. The Hybrid Neutrosophic Decision Optimization (HNDO) framework utilizes Multi-Criteria Decision Analysis (MCDA) and fuzzy logic to make educational decision-making an efficient procedure. In an ordered way, its activities are based on sentiment analysis and topic analysis for potential improvement.

3.5 Phase 5: Hybrid Neutrosophic Decision Optimization (HNDO)

The next part is to apply decision optimization with HNDO in the application of educational institutions. HNDO is an integrated methodology to merge different approaches to decision making, including multi-criteria decision analysis (MCDA) and fuzzy logic with neutrosophic sets to score and optimize performance of the education system based on the feedback survey. To optimize and analyse effectively educational enhancements with respect to social media feedback, a Neutrosophic Quantum Squirrel-Whale Decision Optimization (NQSWDO) is introduced. Figure 3 displays the proposed architecture of the HNDO.

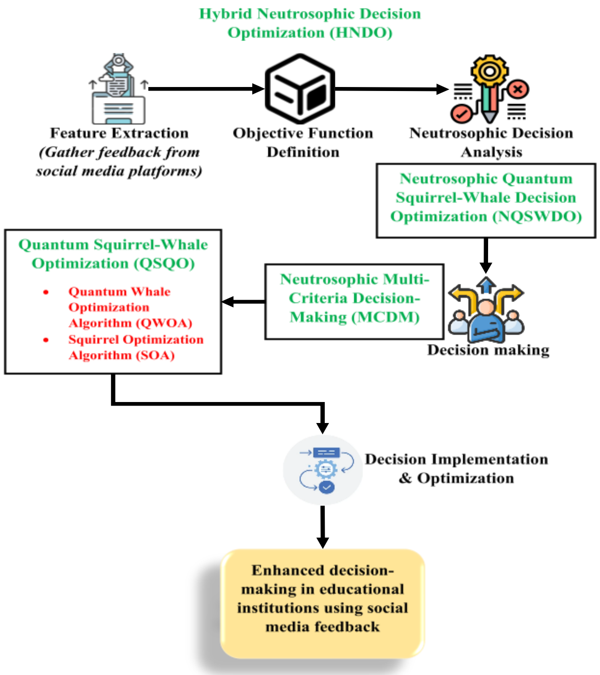

Figure 3. Architecture of the proposed HNDO

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By analysing social media feedback, identify the factors influencing learning environments. Explain the assessment criteria (learner participation, learning effectiveness, and sentiment analysis, interaction quality) to formulate the multi-criteria decision-making (MCDM) problem.

3.5.1 Preliminaries

This section contains the fundamental definitions that are needed.

Definition 1: Fuzzy set

Let X be the universe set of the set of objects, and let a be the elements of the universe set X and Set be the membership using subset of X. The expression for the characteristic function, ξ_{Set} from X to $[0,1]$ is defined in the equation (28).

$$\xi_S(a) = \begin{cases} 1\ if\ and\ only\ if\ a \in Set \\ 0\ if\ and\ only\ if\ a \notin Set \end{cases} \quad (28)$$

The value set [0, 1] indicates membership with 1 denoting it and non-membership with 0 denoting it. If the value set falls inside the interval [0, 1], let A be a fuzzy set. Furthermore, ξ_{Set}:$X\rightarrow$ [0, 1], indicates the degree of membership of elements a in the fuzzy set Set. The more closely an element a's membership value, $\xi_{Set}(a)$, approaches 1, the more element a is associated with the fuzzy set Set.

Definition 2: Interval-Valued Fuzzy Set

An interval-valued fuzzy set is a fuzzy set in which the membership degree is not a single value but an interval $[L(a), U(a)] \subseteq [0,1]$, where $L(a)$ is the lower membership bound and $U(a)$ is the upper membership bound which satisfies the conditions that $\xi_I(a) = [L(a), U(a)]$ and $0 \leq L(a) \leq U(a) \leq 1$.

Definition 3: OWA operator

Ordered Weighted Averaging (OWA) is the technique used to combine multiple input values into one output value as part of the decision-making or aggregation process. The distinguishing aspect of OWA is that instead of taking an average weighted number, it arranges the inputs and assigns a weight to them in order, thus allowing a more flexible kind of aggregation as the largest and smallest values become more important to achieve the output desired.

For a set of n input values $x_1, x_2, \dots, x_n$ and a set of ordered weights $w_1, w_2, \dots, w_n$, the OWA operator is defined in the equation (29):

$$OWA = \sum_{i=1}^{n} w_i \cdot x_i \quad (29)$$

The weights $w_1, w_2, \dots, w_n$ satisfies the conditions such as $0 \leq w_i \leq 1$ for all i, and $\sum_{i=1}^{n} w_i = 1$.

Definition 4: Bhattacharyya distance

The Bhattacharyya coefficient is defined as in the equation (30):

$$B_c(K,V) = \sum_a \sqrt{K(a)V(a)} \quad (30)$$

where the values for which we determine the distance are represented by $K(a)V(a)$. Determine the Bhattacharyya distance by applying the below formula in equation (31).

$$B_d(K,V) = -\ln B_c(K,V) \quad (31)$$

Definition 5: Cosine similarity

Cosine similarity is a metric used to measure how similar two non-zero vectors are in an inner product space. It calculates the cosine of the angle between two vectors, providing a measure of similarity that is independent of their magnitude as shown in the equation (32).

$$CS(A,B) = \frac{A \cdot B}{\|A\|\|B\|} \quad (32)$$

Here, the dot product, $A \cdot B = \sum_{i=1}^{n} A_i B_i$ and the magnitudes $\|A\| = \sqrt{\sum_{i=1}^{n} A_i^2}$ and $\|B\| = \sqrt{\sum_{i=1}^{n} B_i^2}$.

3.5.2 Neutrosophic MCDM

Neutrosophic MCDM methods manage uncertainty and multiple criteria of evaluation in decision-making. They enable decision-makers to evaluate the truth, falsehood, and indeterminacy aspects of feedback for a well-balanced analysis. By using neutrosophic logic, decision-making models provide membership degrees to various categories of feedback for a more complete evaluation. A novel Bhattacharyya-Cosine Average Fuzzy Weight Aggregator (BCAFWA) integrated with the Ordered Weighted Averaging (OWA)-based Technique for Order Preference by

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Similarity to Ideal Solution (TOPSIS) is proposed. Let $A = \{a_1, a_2, a_3, \dots, a_n\}$ indicates the set of different alternatives and $S = \{s_1, s_2, s_3, \dots, s_m\}$ indicates the set of attributes. Also $W = \{\omega_1, \omega_2, \omega_3, \dots, \omega_m\}$ be the corresponding weights for set the sets where $\omega \geq 0$ and $\sum_{i=1}^{m} \omega_i = 1$. And $M = \{m_1, m_2, \dots, m_n\}$ represent a set of decision makers connected to the companies. In this work, we utilize the OWA operator to obtain the decision matrix for two different types of fuzzy sets: single valued and interval valued fuzzy sets. Finally, we apply the proposed novel formula combining Bhattacharyya distance and cosine similarity to find the final decision matrix, which is used to rank the options. The steps and procedure of the proposed BCAFWA is described detailly as follows.

Step 1: Construction of the Decision Matrix in Step Two Utilizing neutrophilic AHP

Every decision-making model that preserves the connection between options and characteristics does so by taking the decision-makers' preferences into account. The linguistic terms provide the foundation for the decision-makers' judgments. While making a decision, balance the criteria while considering uncertainty using Neuromorphic AHP. Describe the Neuromorphic Pairwise Comparison Matrix (NPCM) in Eq. (33). Two fuzzy set numbers are assigned to the linguistic words.

$$D^n = [(\xi_S), (\xi_I)] \tag{33}$$

Where $(\xi_S) = \begin{pmatrix} \cdot & s_1 & s_2 & \cdots & s_m \\ a_1 & d_{11}^k & d_{12}^k & \cdots & d_{1m}^k \\ a_2 & d_{21}^k & d_{22}^k & \cdots & d_{2m}^k \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ a_n & d_{n1}^k & d_{n2}^k & \cdots & d_{nm}^k \end{pmatrix}$ represent the SVFS, and

$(\xi_I) = \begin{pmatrix} \cdot & s_1 & s_2 & \cdots & s_m \\ a_1 & e_{11}^k & e_{12}^k & \cdots & e_{1m}^k \\ a_2 & e_{21}^k & e_{22}^k & \cdots & e_{2m}^k \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ a_n & e_{n1}^k & e_{n2}^k & \cdots & e_{nm}^k \end{pmatrix}$ represents the IVFS.

Here, the following parameter D^n defining the neutrosophic number that defines truthiness (T), falsity (F), and indeterminacy (I). Moreover, the neutrosophic weight vector can be computed using the following Eq. (34).

The truth component (T), falsehood component (F), and indeterminacy component (I) is denoted as per the equation (34):

$$S_T + S_F + S_I = 1 \tag{34}$$

Where, S_T, S_F, S_I are the truth membership, the falsehood membership, and the indeterminacy membership, respectively. In addition, the weighted decision function for the evaluation of feedback is expressed as per the equation (35):

$$D = w_T S_T + w_F S_F + w_I S_I \tag{35}$$

Where, w_T, w_F, w_I are the corresponding weight coefficients to each component.

Step 2: Creating aggregated decision matrix

The defuzzification procedure is done for each fuzzy set after the weight of decision makers is applied to aggregate each decision matrix.

$$D_1^n = \{\textstyle\sum_{i=1}^{m} \Delta_i D^n\} \tag{36}$$

where i represent the number of decision makers.

Step 3: OWA operator

The weight for membership function can be found by using the OWA operator which is mentioned in the equation (2) of definition 3 with the sum of its corresponding columns (rows) for some weight set $W = (w_1, w_2, \dots, w_n)$. Thus, the weighted matrix is obtained.

Step 4: Compute criteria weight

Step 4.1: Normalized matrix

The normalized value r_{ij} for each element is computed as per the equation (37)

$$r_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \tag{37}$$

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Step 4.2: Entropy for each criterion

The entropy for criterion j is defined in the equation (38).

$$E_j = -k \sum_{i=1}^{n} r_{ij} \;\; In\, r_{ij} \quad (38)$$

Step 4.3: Degree of Diversification

The degree of diversification is computed by the equation (39).

$$d_j = 1 - E_j \quad (39)$$

Step 4.4: Criteria weight

Equation (40) is used to calculate the criteria weight.

$$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j} \quad (40)$$

Step 5: Determination of final matrix using BCAFWA aggregator

In this step, the final decision matrix is obtained by using the proposed novel the Bhattacharyya-Cosine Average Fuzzy Weight Aggregator (BCAFWA) is a MCDM operator used to compute aggregated weights of criteria under uncertainty. It integrates Cosine Similarity $(CS(A,B))$ and Bhattacharyya Distance $\left(B_d(K,V)\right)$ to quantify both directional similarity and distributional closeness among criteria. The BCAFWA aggregation formula is defined in the equation (41):

$$W_j = \frac{\sum CS(A,B) + \left(1 - B_d(K,T)\right)}{n} \quad (41)$$

Step 6: Ranking

The TOPSIS technique can now be used to select the best solution to the relevant problem given the attribute data and final matrix. The lowest value is assigned the lowest, and the best selection is defined to the extreme value. In order to minimize subjective biases, a neutrosophic-based optimization function is utilized as per the equation (42):

$$p = \max \sum_{i=1}^{n} (D_i \cdot R_i) \quad (42)$$

Where, D_i is the decision score for feedback, and is its relevance score.

3.5.3 Neutrosophic Quantum Squirrel Whale Decision Optimization (NQSWDO)

Initialization: Supporting this decision is the Neutrosophic Quantum Squirrel Whale Decision Optimization (NQSWDO) method. This distinctive optimization technique makes decisions via techniques grounded in neutrosophic and quantum physics principles, graduating in appending best educational suggestions. Moreover, the parameters are specified using the following Eq. (43),

$$p = \{s_1, s_2 \ldots . . s_N\} \quad (43)$$

Here, the following parameter s_i is an improvement plan in education. Begin positions based on sentiment scores from social media comments.

Step 4: Exploration (Diverse Search - Global Optimization)

By expanding the search space, exploration is responsible for finding new potential solutions. At this step, the SOA utilizes the gliding and jumping movement of squirrels. Thus, the position updation through SOA is given in Eq. (44),

$$x_i(O+1) = x_i(t) + R_1.(x_{best} - x_i(O)) + g \quad (44)$$

Here, $x_i$denotes the current solution of the i -th squirrel, $x_{best}$is the optimal solution found so far, R_1 is a randomly chosen number between 0 and 1. (manages the uncertainty of movement) and the following parameter g is the gliding coefficient, which mimics the capacity to search adaptively. When the squirrels are not sure if food is available, squirrels will jump to random trees (solutions). Choosing Trees at Random for Diversification and it can be mathematically deliberated in the following Eq. (45),

$$x_{new} = x_{rand} + B.(x_{best} - x_{rand}) \quad (45)$$

The parameter B stands for scaling parameter and the randomly selected solutions are denoted asx_{rand}correspondingly. A squirrel employs a guided gliding tool to maximize search efficiency when it encounters a better food source (solution) during the exploratory phase. The squirrel jumps randomly, though, to

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escape local optima and explore other regions of the search space when no improvement is found. The exploration process is made healthy through the impact of factors such as energy levels and seasonal changes on this movement. The optimum solutions achieved by SOA's gliding and jumping behavior are used as the initial population of QWO. Solutions are ordered by fitness, and high-potential individuals only are passed to QWO. Tree-switching behavior in SOA prevents early convergence prior to switching to exploitation.

Step 5: Exploitation (Fine-Tuning - Local Optimization)

It is then followed by exploitation that fine-tunes the optimum solutions found. QWO is utilized here. Whales change positions dynamically in pursuit of the best solution and it can be mathematically deliberated using the following Eq. (46),

$$x_i(O+1) = x'(O) + a.d \tag{46}$$

The most familiar solution is denoted as $x'(O)$, Coefficient of adaptive search is defined as $a$and the distance from the whale to the best solution is denoted as $d = |c.x'(O) - x_i(O)|$. Spiral Search for Local Optimization is accordingly the Whales optimize solutions through a spiral search-based refinement and mathematically it is shown in the following Eq. (47),

$$x_{ew} = x' + e^{(B-L)}.cos(2\Pi L).d \tag{47}$$

Where, $B$is the constant determining shape of a spiral, L is the random number$\in [-1,1]$ and $d$representing the Euclidean distance between the current and best solution. Applying Quantum Perturbation to Alter Solutions it provides a balance between exploration, exploitation is ensured through a quantum update-based, and it is given in Eq. (48),

$$x_{Quatum=}x + \alpha'.\frac{1}{\sqrt{2\Pi\sigma}}e^{-\frac{(x-\mu)^2}{2\sigma^2}} \tag{48}$$

Here, $\alpha'$is the quantum adjustment factor, μ representing the average of optimal solutions and σrandomness control standard deviation. When QWO's encircling and quantum perturbation are unable to further enhance a solution, it is brought back into SOA's tree-switching process in order to investigate alternative routes. The spiral movement of the whale ensures refinement prior to re-evaluation of the solution in the global search space. Mutation-like impact is added, whereby randomly chosen solutions are reverted to SOA's exploration step if stagnation occurs.

Step 6: Dynamic Adaptive Switching Mechanism

A switching probability factor p_{switch}) is employed to switch between SOA and QWO dynamically deliberated using the following Eq. (49),

$$p_{switch} = \frac{Iterationnumber}{MaxIter} \tag{49}$$

If p_{switch}<0.5, the system Favors SOA's exploratory diversity and if p_{switch} ≥0.5, the system Favors QWO's exploitation refinement. This mechanism provides a smooth transition from general social media feedback scanning (SOA) to specific refinement (QWO), maximizing educational decision-making.

Step 7: Hybrid strategy

The last set of assessed social media feedback is calculated based on a hybrid weighted update scheme using Eq. (50),

$$x_{hybrid}(O+1) = W_1.x_{SOA}(O) + W_2 x_{QWO}(O) \tag{50}$$

Where,W_1 and W_2 are dynamic weights with switching priority dynamically between SOA and QWO based on performance, $x_{SOA}(O)$ stands for exploration-driven feedback candidates and $x_{QWO}(O)$ stands for fine-tuned feedback insights. The suggested NQSWO model successfully combines Neutrosophic AHP, SOA, and QWO for improving educational settings via maximized social media feedback evaluation. Relying on exploration, exploitation, and adaptive switching, the method is ensured to provide a balanced and data-orientated decision-making process to create better learning experiences and institutional development.

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Algorithm 1: Algorithm for NQSWO

Step 1: Define the Problem and Select Criteria

```
def define problem ():
  criteria = ['learner participation', 'learning effectiveness', 'sentiment analysis', 'interaction quality']
    return criteria
```

Step 2: Construct Decision Matrix Using Neutrosophic AHP

```
def construct_decision_matrix (criteria):
    NPCM = compute_pairwise_matrix (criteria)
    NWV = compute_neutrosophic_weight (NPCM)
    return NWV
```

Step 3: Initialize NQSWO Algorithm

```
def initialize_NQSWO (pop_size):
    population = initialize population (pop_size)
    return population
```

Step 4: Exploration using SOA

```
def exploration_SO (population):
    for squirrel in population:
        if random () < 0.5:
            new_position = glide(squirrel)
        else:
            new_position = jump(squirrel)
        update population (population, new_position)
    return population
```

Step 5: Exploitation using QWO

```
def exploitation_QWO (population):
    for whale in population:
        if random () < 0.5:
            new_position = encircle(whale)
        else:
            new_position = spiral_search (whale)
        apply_quantum_perturbation (new_position)
    return population
```

Step 6: Dynamic Adaptive Switching Mechanism

```
def adaptive_switching (population, switch_prob):
    if switch_prob < 0.5:
```


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return exploration_SO (population)
else:
return exploitation_QWO (population)
Step 7: Hybrid Strategy
def hybrid_decision (population):
final_decision = compute_hybrid_weighted_update (population)
return final_decision

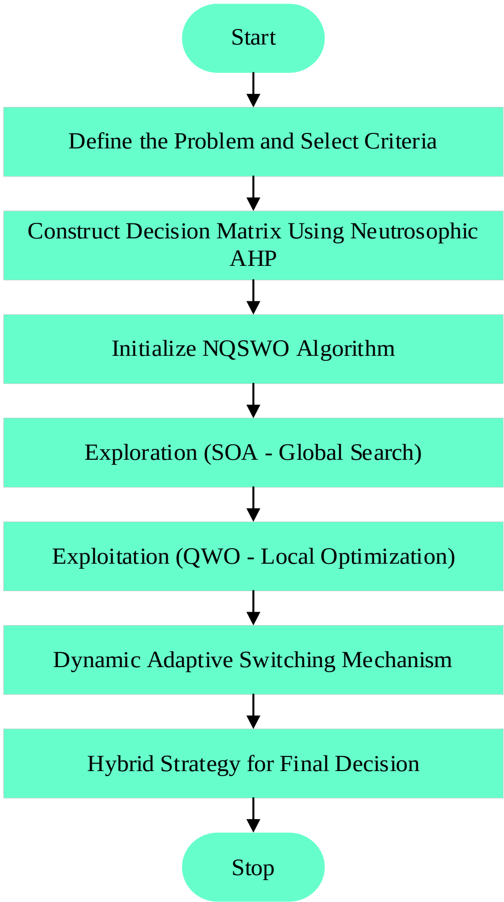

Figure 4. Workflow of NQSWO

The key concerns in education are represented through a VGG-Darknet detection model. Particularly in deep learning, this system enables the even excision of critical topics, making entire problems confronted by the education institutions seen and explored extremely effectively.

3.6 Phase 5: VGG-Darknet Detection Model for Key Concern (topics) Detection

Although NSF offers sentiment classification, it does not focus on specific concerns (courses difficulty, grading policy, or faculty behavior for example). To achieve this, we proposed a novel VGG-Darknet Detection Model for identifying key concerns in student feedback.

3.6.1 Attention-Augmented VGG-Darknet Detection Model

The extracted features (textual embeddings) are fed into the Attention-Augmented VGG-Darknet Detection Model (shown in Fig.4), which acts as the hierarchical feature extractor. The VGG-16 components extract the fundamental linguistic patterns as well as the low-level texture features, while the high-level contextual representations as well as the deep semantic structures are captured using the **Darknet-53 Component**. The soft-

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thresholding within the **Residual Shrinkage Building Unit (RSBU)** assist in enhancing the quality of the features by means of reducing the noises**.** Onto the textual representations, the spatial and channel attention of the **Attention-Augmented Feature Pyramid** are applied in order to enrich the feature importance.

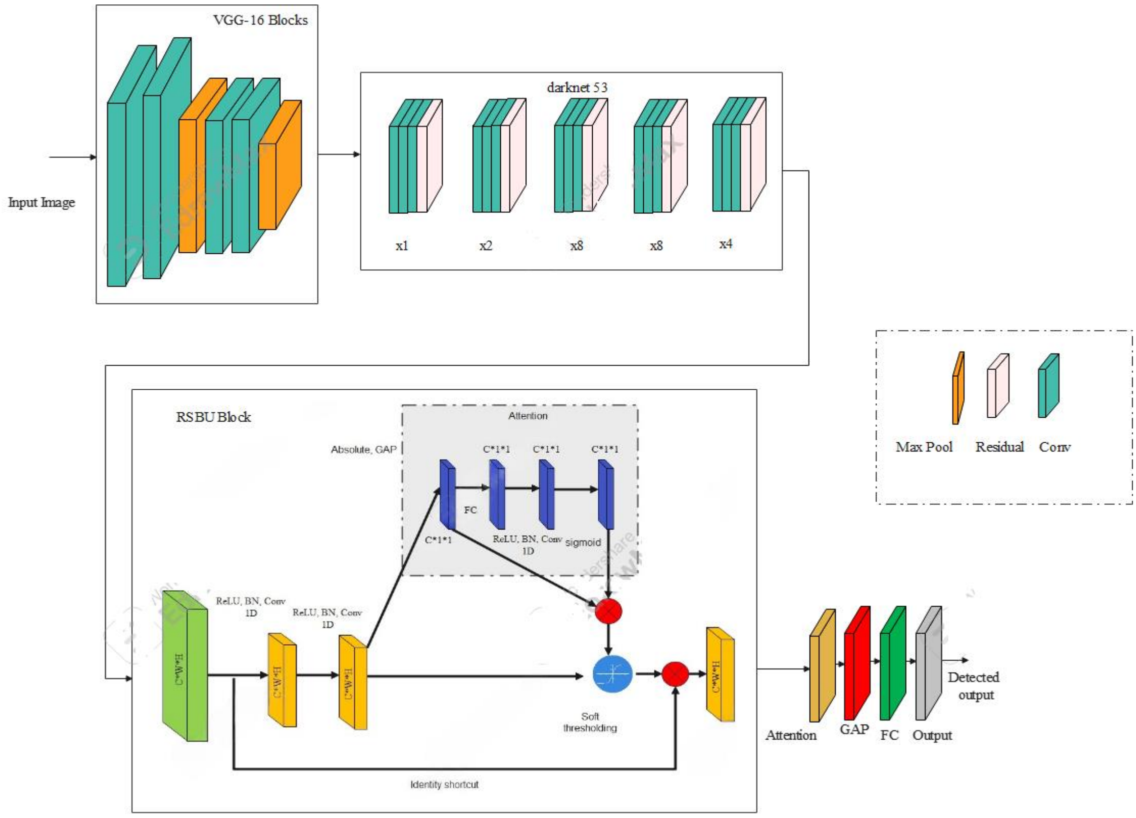

Figure 5. Architecture of the Attention-Augmented VGG-Darknet Detection

For a given data feature$X$, the convolution operation in VGG-16 can be expressed as:

$$f_i^{(l)} = \sigma\left(\sum_j f_j^{(l-1)} \cdot W_{i,j}^{(l)} + b_i^{(l)}\right) \tag{51}$$

where $f_i^{(l)}$ denotes the output feature at position i in layer$l$, $W_{i,j}^{(l)}$ is the weight matrix, $b_i^{(l)}$ denotes the bias and σ denotes the activation function (ReLU)

Subsequent to the VGG-16 layer, the presented features are further fed into Darkent-53 in order to carry out the even deeper and more complicated feature representation (contextual dependencies between extracted topic-related features). It employs **residual learning**, ensuring deep semantic features are preserved.

The transformation in a residual block within Darknet-53 is given by:

$$H(X) = F(X, \{W_i\}) + X \tag{52}$$

where $H(X)$ denotes the output of the residual block, $F(X, \{W_i\})$ represents the convolutional transformations on X with weight set $\{W_i\}$, X indicates the input to the residual block.

The goal of the Residual Shrinkage Building Unit (RSBU) is to process the feature map generated from Darknet-53 in a manner that minimizes the noise yet retains the important characteristics of the features. RSBU utilizes soft-thresholding, which is a method of filtering the feature map that does not eliminate the important elements used for topic modelling but suppresses only the noise elements.

The soft-thresholding function $S(x; \lambda)$ in RSBU can be mathematically expressed as:

$$S(x; \lambda) = sign(x) \cdot max(|x| - \lambda, 0) \tag{53}$$

where x denotes the input feature, λ indicates a learnable threshold parameter that adapts to the noise level in the data.

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The Attention-Augmented Feature Pyramid layer is a complex mechanism that incorporates both spatial and channel-wise attention. **Channel Attention** enhances **critical topic dimensions** by weighting feature importance. Channel attention weights $M_c$for each feature map can be computed as:

$$M_c = \sigma\left(W_2 \cdot \left(RELU\left(W_1 \cdot GAP(F)\right)\right)\right) \quad (54)$$

where F represents the input feature map, $GAP(F)$ denotes the Global Average Pooling of F, W_1 and W_2 are learnable weights, σ represents the sigmoid function to obtain attention weights between 0 and 1. **Spatial Attention** focuses on important word sequences in the text. Spatial attention weights M_s are computed by applying convolutional filters across the spatial dimension:

$$M_s = \sigma\left(f^{7\times7}\left(F_{avg}; F_{max}()\right)()\right) \quad (55)$$

where F_{avg} and F_{max} are the channel-wise average and maximum pooling results of F, $f^{7\times7}$a convolutional filter with a 7×7 kernel. After the attention-enhanced feature extraction, the obtained feature map is fed to a Global Average Pooling layer. This layer pools the regional information across the entire feature map by calculating the mean of the spatial size of each individual feature map and outputting a single vector. This step, which reduces the overall number of dimensions, helps in bringing down the unwieldy feature representation into simpler dimensional forms without losing critical features. Pooling helps avoid risks associated with overfitting since it gives a less detailed representation of the high-level features. This improvement in the generality of the model also leads to lower resource consumption.

The processed feature vector from the GAP is then forwarded to a dense layer, which provides the last feature combination and formats the data for classification. Then classification of data is performed by providing a softmax layer to compute and generate the probability of the classes possible, assigning the class with maximum probability as the prediction of the model. It is these fully connected and softmax layers that provide the necessary interpretation of the deep feature representations obtained from the prior layers and output categorization of the features. The **final topic representation** is obtained using **Global Average Pooling (GAP)**, reducing dimensionality while preserving contextual richness:

$$P(y = c|z) = \frac{exp(W_c \cdot z + b_c)}{\sum_j exp(W_j \cdot z + b_j)} \quad (56)$$

where W_c and b_c signifies the weights and bias for class c, z denotes the consolidated feature vector from the GAP layer.

3.7 Reinforcement Learning with Deep Q-Network (DQN) for Dynamic Topic Intervention

Reinforcement learning helps the system, namely Deep Q-Network (DQN), to allow dynamic intervention in the topic discussion. Enhancing real-time adaptabilities, this framework lets the system readjust with reference to the importance of different emerging concerns as they come through their own social media pretensions and feedback data. Traditional topic modelling techniques, such as Latent Dirichlet Allocation (LDA) and Non-Negative Matrix Factorization (NMF)**,** generate static topic representations, failing to **adapt dynamically** to evolving discussions, emerging trends, and shifting user interactions. To overcome this limitation, a Reinforcement Learning-based Dynamic Intervention Module is introduced. This module optimizes topic classification, clustering, and weighting by learning from real-time feedback. Reinforcement Learning (RL) is an effective approach for dynamically refining topic modelling by optimizing interventions based on user engagement, sentiment, and feedback. However, RL models—especially deep learning-based ones **like** Deep Q-Networks (DQN)**—**are often criticized for their **black-box nature**, making it difficult to understand why certain topics are modified, merged, or re-weighted. To address this, we integrate Explainable AI (XAI) techniques, such as Local Interpretable Model-agnostic Explanations (LIME) and Shapley Additive Explanations (SHAP), ensuring that topic classification and interventions are both adaptive and transparent**.** This discussion explores how DQN dynamically updates topic **structures** and how XAI techniques provide interpretability, ultimately fostering trust in AI-driven topic modeling systems**.**

3.7.1 State Representation in Topic Modelling

Defining the State Space: A Reinforcement Learning environment should, therefore, be able to represent an appropriately structured state space capturing all of the key features of an environment. The state representation pertaining to the dynamic topic model implementing intervention is devised from:

1. Extracted Topic Embeddings: A multi-dimensional space-type representation of a topic from a deep learning-based feature extractor (VGG-Darknet).

2. Metadata Features: Contextual factors include Sentiment analysis, discourse type, and topic relevance.

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3. Historical Trends of User Feedback: Captures user interaction metrics such as click-through rates, time spent on topics, and level of engagement to potentially refine topic relevance dynamically.

At time t, the state is represented as:

$$S_t = \{\hat{F}, C_t, U_t\} \quad (57)$$

where:

•$\hat{F}$ is a representation of extracted multi-domain topic embeddings.

•C_t contains contextual metadata (e.g., time-sensitive keywords, domain-specific markers).

•U_t captures historical user interactions, and performance measurement is done via behavioral metrics.

3.7.2 Defining RL Actions for Dynamic Topic Optimization

At each Timestep, the RL choose an action towards improving topic classification.

Actions are expressed as a discrete set: A={a1,a2,......,an}

Where:

- a1 = Merge topics with high semantic similarity.
- a2 = Split topics with low coherence scores.
- a3 = Feature reweighting using self-attention mechanisms.
- a4= Change the topic modeling method dynamically

where actions include:

1. **Refining topic clusters** – Merging or splitting topics based on semantic similarity.
2. **Re-weighting topic importance** – Adjusting the weight of certain topics based on engagement and sentiment trends.
3. **Enhancing feature extraction techniques** – Modifying word embeddings or topic coherence measures to improve accuracy.

For example, if a trending topic emerges, the RL agent **dynamically increases its weight**, ensuring real-time adaptability.

3.7.3 Reward Function Design: As for the reward function, it was established to optimize topic quality on 3 dimensions of performance:

Mathematical Formulation of the Reward Function

The total reward at time t is calculated as

$$R_t = \omega_1 . C_t + \omega_2 . S_t + \omega_3 . C_3 \quad (58)$$

where: -ω_1, ω_2 and ω_3 are the scaling coefficients that help prioritize different reward components. The Topic Coherence Score (C_t)- which is a measure of semantic consistency within topics. The Sentiment Alignment Score (S_t) accounts for **sentiment alignment** (matching discussion tone with audience sentiment). User Engagement Score (U_t) captures **user engagement trends** (interaction metrics like clicks, shares, and dwell time). In addition, ω_1 are **scaling coefficients** adjusting the contribution of each factor.

Deep Q-Network (DQN) for Policy Optimization in Topic Interventions

This uses Q-Value approximation to optimize intervention policies based on Deep Q- Network (DQN) operations that guide the RL agent in choosing the best action at each timestep.

$$Q(S_t, A_t) = R_t + \gamma \max_{A'} Q(S_{t+1}, A') \quad (59)$$

where:

- γ is the **discount factor** controlling the influence of future rewards.
- A' is the next action maximizing the Q-value.

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DQN Training Process

1. **Experience Replay**: Stores past transitions ($S_t A_t$, R_t, S_{t+1}in memory to **break correlation** between consecutive learning steps.
2. **Target Network Stabilization**: Maintains a separate **target network** for Q-value updates.
3. **Loss Function**: The Q-value is optimized using **Mean Squared Error (MSE)** between estimated and target Q-values:

$$L(\theta) = E[(R_t + \gamma . A' . maxQ(S_{t+1}, A') - \max_{A'} Q(S_{t+1}, A') \quad (60)$$

Finally, the feedback analysis, interpretation, and strategic decision-making processes. The findings obtained from previous phases are then combined into actionable policy recommendations so that educational improvements can be executed effectively.

3.8 Feedback Analysis and Interpretation

After processing the social media feedback through NSF and analysing it through HNDO, interpretation of the findings comes next. The feedback is analysed to derive actionable insights for the school. This analysis consists of:

- **Sentiment Trends:** Determining the overall sentiment trend over time (positive, negative, or neutral) and the identification of patterns in feedback.
- **Key Issues and Areas for Improvement:** Identifying most frequently cited problems by users, including unhappiness with teaching standards, administrative support, or infrastructure.
- **Success Stories:** Identifying areas where the educational institution shines, including student participation, innovative pedagogy, or facilities in good repair.

3.9 Decision Making and Implementation

The last step of the methodology is to make decisions based on the conclusions derived from the sentiment fusion and optimization process. The decision-makers, including educational administrators, instructors, and policymakers, utilize these conclusions to introduce changes in the learning environment. The decisions are to be in line with the priorities determined by HNDO and is to focus on areas of greatest influence on student satisfaction and overall performance. The enforcement of such decisions include:

- **Curriculum Changes:** Changing courses or teaching methods to tackle issues highlighted by students.
- **Resource Re-Allocation:** Shifting resources towards improvement in areas such as infrastructure, technology, or training staff.
- **Policy Adjustments:** Revamping or renewing institutional policies through feedback to better the learning experience.

3.10 Continuous Feedback Loop

Due to the dynamic and constantly changing educational environment, an ongoing feedback mechanism needs to be established. Ongoing evaluation in real-time via social media provides the opportunity for adjustments based on feedback. Thus, the method is iterative-regular data collection, sentiment fusion, decision optimization, and implementation phases, in which institutions continue to be responsive to the fluid needs and expectations of students.

The HNSDF framework that combines NSF and HNDO is one that is strong and thorough enough to analyse and improve educational settings from social media opinions. To accommodate the intrinsic uncertainty and indeterminacy in the opinions, the methodology allows for effective sentiment analysis as well as informed decision-making using data. As it continually monitors and optimizes, institutions establish more adaptive, responsive, and effective settings that benefit both staff and students. The performance evaluation of the proposed model is explained in the next section.

4. Result and Discussion

The performance score attained by the suggested model is discussed in this section. Moreover, this section provides a comparison analysis, metrics evaluation, and experimental setup of the suggested model. The performance score attained by the proposed model is compared with the existing models such as MADM [17], SVNN-VIKOR [19], SVM [22] and CSCL [23] for validating the performance of the proposed model.

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4.1 Experimental setup

The Python environment is employed to implement the experiment. In order to ensure effective model assessment, the data is separated into 70% for training and 30% for evaluation. In order to assess accuracy and reliability, several performance measures are tested. The setup ensures a balanced training and validation method. Preprocessing methods are implemented to clean up and normalize the data in a bid to enhance speed. To enhance effectiveness, the model is optimized with parameters. Finally, the results are evaluated in order to determine how effectively the model processes social media comments.

4.2 Metrics evaluation

The performance metrics such as accuracy, precision, sensitivity, and specificity, F-score, NPV, MCC, FNR and FPR are measured for calculating the performance of the suggested model. Following table 2 shows the Analysis of performance metrics.

Table 2: Analysis of performance metrics

Metric	**Description**	**Formula**
Accuracy	Measures how well the model correctly identifies relevant and irrelevant feedback. Higher accuracy means better overall performance.	$A = \frac{t_p + t_n}{t_p + f_p + t_n + f_n}$
Precision	Indicates how many of the predicted relevant feedback points are actually correct. Higher precision ensures only useful feedback is selected.	$p = \frac{t_p}{t_p + f_p}$
Sensitivity (Recall)	Measures how well the model identifies all relevant feedback. Higher sensitivity means fewer important insights are missed.	$R = \frac{t_p}{t_p + f_n}$
Specificity	Measures how well the model filters out irrelevant feedback. Higher specificity reduces false positives.	$S = \frac{t_n}{t_n + f_p}$
F-Score	Balances precision and sensitivity to give an overall measure of the model's effectiveness in selecting relevant feedback.	$F - score = 2 \times \frac{P \times R}{P + R}$
MCC (Matthews Correlation Coefficient)	Evaluates the model's overall quality, considering all errors. A higher MCC indicates better classification performance.	$MCC = \frac{(t_p . t_n - f_p . f_n)}{\sqrt{(t_p + f_p)(t_p + f_n)(t_n + f_p)(t_n + f_n)}}$
NPV (Negative Predictive Value)	Measures how many of the predicted irrelevant feedback points are actually correct. A high NPV ensures unnecessary information is minimized.	$NPV = \frac{t_n}{t_n + f_n}$
FPR (False Positive Rate)	Indicates how often irrelevant feedback is incorrectly classified as relevant. Lower FPR means fewer unnecessary feedback suggestions.	$FPR = \frac{f_p}{f_p + t_n}$
FNR (False Negative Rate)	Measures how often relevant feedback is missed by the model. Lower FNR means important feedback is not overlooked.	$FNR = \frac{f_n}{f_n + t_p}$

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4.3 Performance of the proposed model

The comparison of performance between Dataset-1 and Dataset-2 indicates that Dataset-2 performs better than Dataset-1 in all the important metrics, which implies a stronger and more accurate model when trained on Dataset-2. The accuracy of the model for Dataset-2 is 99.62%, which is much greater than 98.08% for Dataset-1, which implies improved overall classification. In addition, precision (99.81%) and sensitivity (99.54%) for Dataset-2 are higher than those for Dataset-1 (98.81% and 98.54%, respectively), indicating that the model efficiently reduces false positives and false negatives. The specificity (98.96%) is higher for Dataset-2 than 97.28%, i.e., it is better at identifying irrelevant instances correctly. The F-Score (99.38%) and MCC (98.85%) signify better precision and recall balance, demonstrating the ability of the model to deal with varied data. Moreover, Dataset-2 has a very high NPV (99.91%), minimizing misclassifying irrelevant instances, and has lesser FPR -1.51% and FNR - 0.46%, reflecting fewer errors of classification. Overall, the model performs better on Dataset-2 and is more appropriate for accurate predictions and decision-making. Thus, the Performance score attained by the proposed model by using dataset 1 and dataset 2 is shown in table 3.

Table 3: Performance score attained by the proposed model by using dataset 1 and dataset 2

Metrics	Performance score attained by Dataset -1	Performance score attained by Dataset -2
Accuracy	0.98082	0.99624
Precision	0.98816	0.99815
Sensitivity	0.98539	0.99542
Specificity	0.97286	0.98963
F-Score	0.98945	0.99387
MCC	0.97981	0.98852
NPV	0.98458	0.99912
FPR	0.02791	0.01512
FNR	0.01941	0.00462

4.4 Comparison analysis

Important metrics such as Accuracy, Precision, Sensitivity, Specificity, F-Score, MCC, NPV, FPR, and FNR are applied to compare the performance of the various models, including MADM, SVNN-VIKOR, SVM, CSCL, and the proposed model. With 98.08% as the highest accuracy, the proposed model outperforms others, achieving higher accuracy than SVNN-VIKOR (96.93%), SVM (95.91%), MADM (95.74%), and CSCL (94.48%). The high accuracy of the proposed model indicates the excellent ability of the model to classify relevant social media comments, hence making it a wonderful learning environment improvement tool. The proposed model performs a precision of 98.82%, which calculates the model's ability to positively identify cases accurately. MADM (96.00%), SVNN-VIKOR (96.48%), SVM (96.44%), and CSCL (95.69%) follow thereafter. The high precision of the proposed model ensures that there are not many unwanted comments wrongly declared as useful ones, improving social media evaluation's validity. Moreover, the proposed model boasts the best Sensitivity (Recall) of determining the extent of detection of positive true cases with a rate of 98.54%, by far better compared to MADM (96.65%), SVNN-VIKOR (96.22%), SVM (95.08%), and CSCL (94.97%). This demonstrates how the model can pull out useful information from social media discourse in a learning context.

Table 4: Performance analysis for dataset-1

Model	Accuracy	Precision	Sensitivity	Specificity	F-Score	MCC	NPV	FPR	FNR
MADM [17]	0.95742	0.96009	0.96659	0.95681	0.96574	0.93684	0.95957	0.04867	0.03941
SVNN-VIKOR [19]	0.96933	0.96482	0.96223	0.95712	0.96851	0.94951	0.96894	0.04796	0.03591
SVM [22]	0.95918	0.96448	0.95081	0.94491	0.95948	0.94884	0.95972	0.04948	0.04294
CSCL [23]	0.94483	0.95689	0.94967	0.94952	0.94691	0.93967	0.95067	0.05391	0.05941
Proposed	0.98082	0.98816	0.98539	0.97286	0.98945	0.97981	0.98458	0.02791	0.01941

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With a 97.29% specificity score, the proposed model is superior to MADM (95.68%), SVNN-VIKOR (95.71%), SVM (94.49%), and CSCL (94.95%), which is a significant parameter in avoiding false positives. Proper classification of unfavourable cases ensures that unrelated social media comments will not mislead school ratings. In addition, the proposed model possesses the highest F-Score (98.95%), which is a compromise between sensitivity and precision, followed by MADM (96.57%), SVNN-VIKOR (96.85%), SVM (95.94%), and CSCL (94.69%). This demonstrates how the proposed methodology finds a good balance between reducing misclassification and recognizing relevant feedback. The proposed model achieves the highest MCC, overall classification performance, at 97.98%, significantly surpassing MADM (93.68%), SVNN-VIKOR (94.95%), SVM (94.88%), and CSCL (93.96%). A high MCC indicates the strength of the proposed method in evaluating social media input through the identification of a strong relationship between real and expected classifications. Moreover, the proposed model's NPV, which measures the accuracy of negative classifications, is greater at 98.46% compared to MADM (95.95%), SVNN-VIKOR (96.89%), SVM (95.97%), and CSCL (95.06%). By effectively eliminating redundant feedback, the proposed model ensures high-quality data for educational analysis. Also, the proposed model possesses the least FPR and FNR, which measure the error rates of the model, at 2.79% and 1.94%, respectively. On the other hand, CSCL possesses the highest error rates with an FPR of 5.39% and a FNR of 5.94%, whereas MADM possesses an FPR of 4.87% and a FNR of 3.94%, SVNN-VIKOR presents 4.79% and 3.59%, and SVM presents 4.94% and 4.29%. The proposed model is the most reliable choice for accurately analyzing social media feedback due to its low FPR and FNR, which indicate how well it can minimize missed classifications and false alarms. Overall, the proposed model scores extremely high on all the standards, way ahead of MADM, SVNN-VIKOR, SVM, and CSCL. Due to its low FPR and FNR, and high accuracy, precision, sensitivity, specificity, F-Score, MCC, and NPV, it is the most appropriate one for assessing social media input in academic environments. Educational institutions can enhance learning experiences and make improved decisions by this advanced model in order to gain a better grasp of student engagement, learning habits, and sentiment analysis.

Table 5: Performance analysis for dataset-1

Model	**Accuracy**	**Precision**	**Sensitivity**	**Specificity**	**F-Score**	**MCC**	**NPV**	**FPR**	**FNR**
MADM [17]	0.96412	0.95874	0.97015	0.95127	0.96932	0.94721	0.96528	0.05742	0.03812
SVNN-VIKOR [19]	0.97724	0.97245	0.97436	0.96638	0.97382	0.95478	0.97023	0.04638	0.02187
SVM [22]	0.96814	0.97328	0.96237	0.95519	0.96842	0.95092	0.96874	0.04815	0.04128
CSCL [23]	0.95985	0.96214	0.95163	0.95192	0.95478	0.94037	0.96518	0.05187	0.04512
Proposed	0.99624	0.99815	0.99542	0.98963	0.99387	0.98852	0.99912	0.01512	0.00462

In terms of enhancing learning environments based on social media feedback assessment, the proposed model performs better than the rest of the models, such as MADM, SVNN-VIKOR, SVM, CSCL, and the proposed model. It performs better than MADM (96.41%), SVNN-VIKOR (97.72%), SVM (96.81%), and CSCL (95.98%) since it achieves the highest accuracy (99.62%). Due to its excellent accuracy, the proposed model performs better than the rest of the models in precisely classifying feedback as relevant or irrelevant. The Proposed model takes the lead again with 99.81% in accuracy, which measures the percentage of estimated relevant feedback points that are actually correct. SVNN-VIKOR (97.24%), SVM (97.32%), MADM (95.87%), and CSCL (96.21%) take the next places. Such high accuracy ensures that marked helpful comments are actually useful in improving learning chances. The recommended model has the highest sensitivity (recall) of 99.54%, compared to MADM (97.01%), SVNN-VIKOR (97.43%), SVM (96.23%), and CSCL (95.16%). This shows that the recommended model is excellent in identifying all relevant feedback, which reduces the chances of missing important information. Likewise, the proposed model is most specific (98.96%), which measures how effectively the model prevents false positives, ensuring extraneous feedback is properly filtered out. The model also possesses the highest F-Score, a compromise between sensitivity and precision, of 99.38%, higher than SVNN-VIKOR (97.38%), SVM (96.84%), MADM (96.93%), and CSCL (95.47%). Due to this, the proposed methodology is the most reliable for effectively handling social media comments. Its MCC (Matthews Correlation Coefficient) score of 98.85% further complements its high overall performance. Following table 4 shows the Performance analysis for dataset-1 and the following table 5 shows the Performance analysis for dataset-2.

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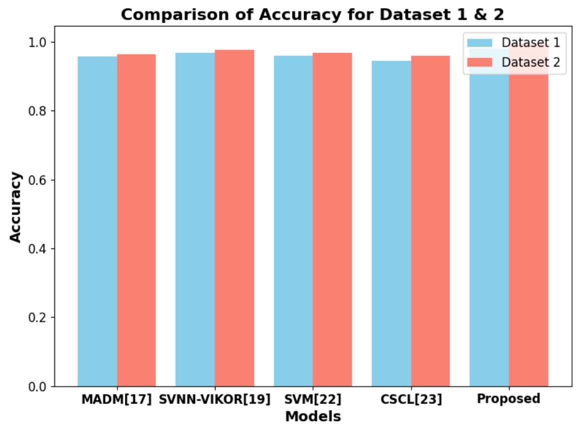
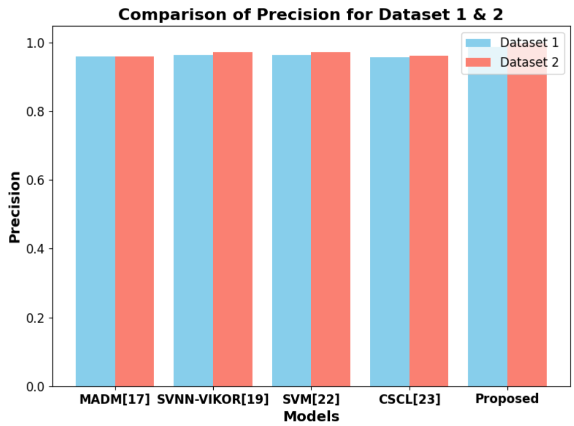
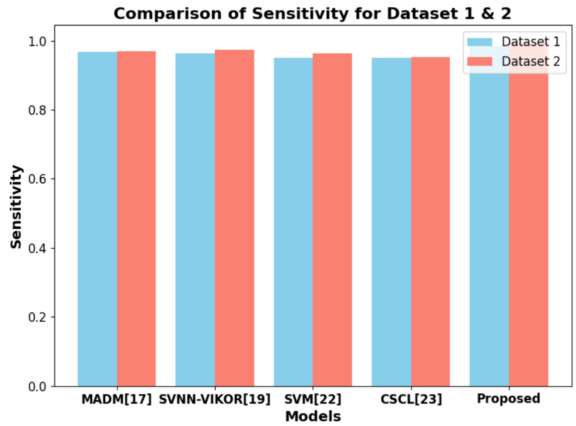


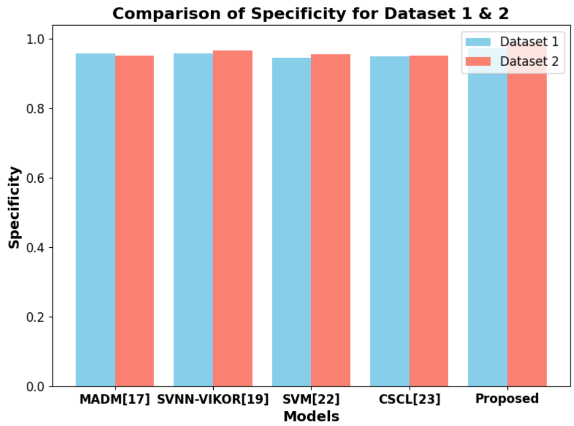
(a) Comparison of accuracy



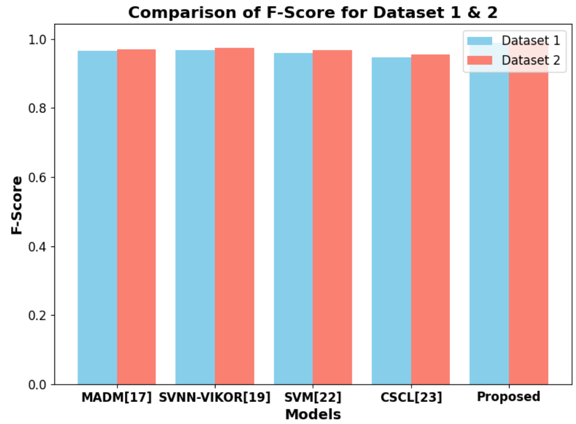
(b) Comparison of Precision



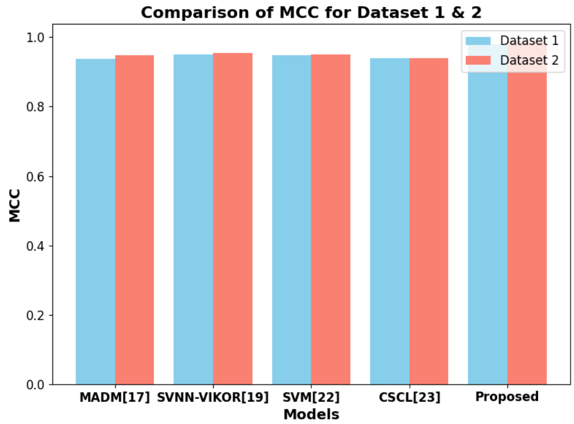
(c) Comparison of Sensitivity



(d) Comparison of Specificity



(f) Comparison of F-score



(g) Comparison of MCC

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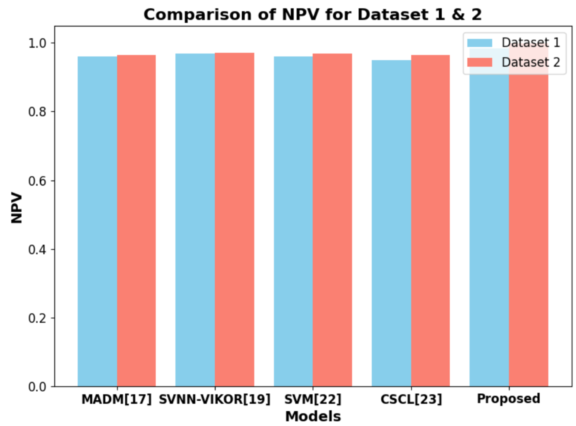
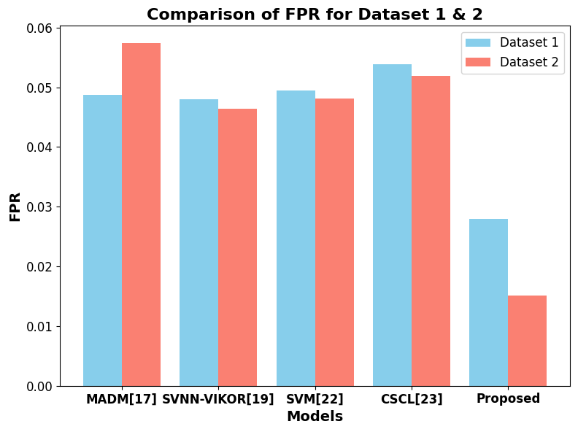
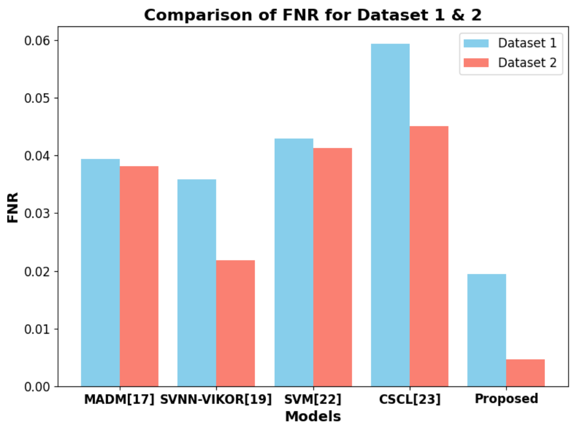




(g) Comparison of NPV

(h) Comparison of FPR



(i) Comparison of FNR

Figure 6. Graphical representation performance comparison for both dataset 1 and dataset 2

In addition, the proposed model rarely misclassifies unimportant feedback as significant, with the highest NPV of 99.91%. It is also best at avoiding classification errors, having the lowest FPR of 1.51% and the lowest FNR of 0.46%. Overall, the proposed approach performs better than any other in accurately and effectively evaluating social media comments in the classroom. Its superb recall and accuracy guarantee that vital information is noted and extraneous data is avoided. Decision-making within learning spaces can be greatly enhanced by this, which will enhance student interest and enhance learning outcomes.

4.5 Local Interpretable Model-Agnostic Explanations (LIME) analysis

Through enhanced transparency and interpretability of social media feedback assessment, LIME is employed in enhancing learning environments. Through providing reasons for every prediction, it helps to understand how a machine-learning model classifies feedback. Educators can ensure that vital student information is not overlooked by employing LIME to identify significant variables influencing feedback classification. This raises confidence in AI-based analysis, making it easier to make better decisions for enhancing teaching strategies and content. LIME simplifies the process of improving engagement and learning outcomes by making social media feedback analysis easier to comprehend.

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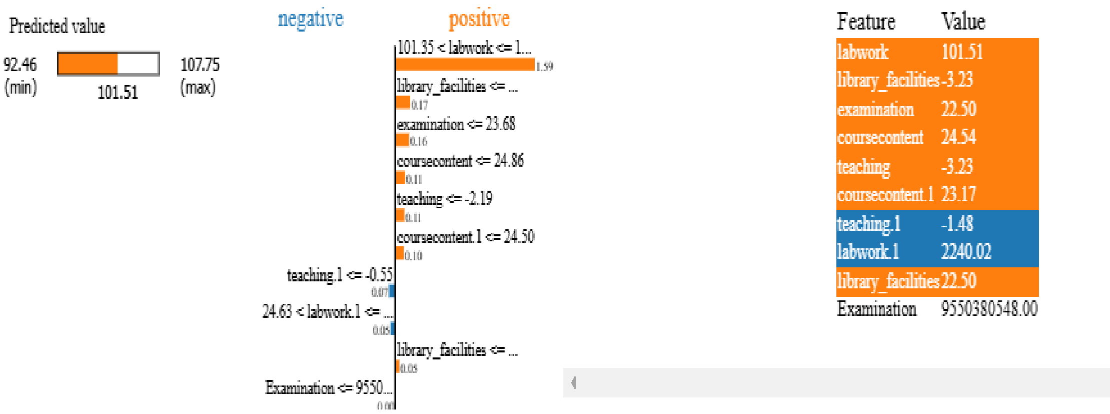

Figure 7. Lime analysis

Within the evaluation of social media feedback in academic contexts, the LIME analysis represented in the figure 6 provides a clear explanation of how different elements go towards creating the expected value. The range of expected value is indicated in the left region, and the most significant positive and negative contributors are emphasized in the middle region. The prediction is highly dependent on factors such as lab work, library facilities, examination, course material, and teaching. The importance of the feature is also measured in the right panel, which shows both positive (orange) and negative (blue) contributions. For instance, teaching (-3.23) contributes negatively to the outcome, while lab work (101.51) contributes significantly positively. By identifying places that enhance or worsen students' experiences, these findings help educators refine their scholarly strategies and design a more effective and engaging learning environment.

5 Conclusion

To improve the education delivery performance using social media feedback analysis, a multi-step approach was applied based on modern natural language processing (NLP), sentiment analysis, and decision optimization techniques. At first, data collection followed by various pre-processing like tokenization, stop word removal, stemming/lemmatization, and emoji handling was done for textual refinement. Then comes feature extraction, which utilizes TF-IDF and sentiment-based attributes, LSA topic modelling, user engagement metrics in order to derive valuable knowledge and insight. The Neutrosophic Sentiment Fusion (NSF) model is finally applied to classify sentiment, thus ensuring better accuracy in uncertain environments. In addition to that, Hybrid Neutrosophic Decision Optimization (HNDO), which entails multi-criteria decision analysis (MCDA) and fuzzy logic with neutrosophic sets, has been used to optimize educational performance. For further sharpening such decisions, the Neutrosophic Quantum Squirrel-Whale Decision Optimization (NQSWDO) is brought in, corresponding Neutrosophic MCDM with fuzzy techniques for more precise evaluation. Not only but also, advocates the VGG-Darknet Detection Model in vital concern detection from social media discussions, but reinforcement learning through Deep Q-Network (DQN) would also involve the dynamic intervention of topics. Finally feedback analysis, interpretation, and actionable decision making take place.

Results and Conclusion: The framework presents high classification performance on two datasets and thus gains remarkable accuracy (0.98082 and 0.99624) along with precision (0.98816 and 0.99815), sensitivity (0.98539 and 0.99542), specificity (0.97286 and 0.98963), F-score (0.98945 and 0.99387), MCC (0.97981 and 0.98852), and NPV values (0.98458 and 0.99912). The rates of false positives (FPR) and false negatives (FNR) remain low, indicating reliability. Limitations of the model include dependence on data diversity, high computational complexity due to neutrosophic and quantum processes, as well as requiring real-time adaptability. Future work will be directed toward a study in real-time analytics, explainable AI for interpretability, and broader datasets to improve the applicability of educational enhancement strategies.

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