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Article

Neuro-Fuzzy Decision System for Student Stream Selection

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Abstract: Choosing an appropriate academic stream plays a crucial role for students in shaping their careers. However, choosing the right academic stream may be influenced by various factors related to uncertainty and subjectivity, such as academic performance, parent's influence, socioeconomic background, career goals, and personal skills. A Neuro-Fuzzy Decision System (NFDS), which operates using Adaptive Neuro-Fuzzy Inference System (ANFIS), can assist in offering an intelligent recommendation for selecting a suitable student stream. Fuzzy logic coupled with learning capability of neural networks allows modeling uncertainties and incorporation of expert knowledge in addition to taking into account historical data on education. The study uses a dataset that includes features related to academic, demographic, socioeconomic, parental, and career information obtained through questionnaires. NFDS uses fuzzy membership functions, rules, and learning techniques to recommend one out of three streams – Science, Commerce, and Arts. Performance testing of ANFIS-based NFDS is evaluated against random forest, decision tree, xgboost, support vector machine, and artificial neural network algorithms. The suggested ANFIS method was able to reach the highest accuracy of 94.00%, along with having a precision of 94.74%, recall of 83.72%, F1 score of 88.89%, and AUC value of 0.957. Additionally, feature importance analysis highlighted that communication skills, decision-making freedom in the career path, financial aid, and social background were some of the key attributes when it comes to selecting the right streams. The findings indicated that the suggested neuro-fuzzy methodology is able to provide accurate recommendations.
Keywords: Stream Selection; Student Stream Selection, ANFIS, Neuro-Fuzzy Decision System, Educational Data Mining, Career Guidance, Explainable Artificial Intelligence,

1. Introduction

Choosing a stream in high school or higher secondary school is one of the most important decisions a learner makes during their educational career. The choice of streams is likely to influence the student's future academic and professional paths and may even impact their socio-economic status later in life. At some point in their education, students must make decisions regarding which stream they wish to pursue, such as Science, Commerce, or Arts/ Humanities, with little knowledge of the working world and their own abilities.

The choice of stream is not always a rational or objective exercise. Rather, it is a function of various influences which include academic success, interests, parental wishes, social status, peer pressure, organizational pressures, and psychological pressures among others. Such influences can be largely qualitative, subjective, and uncertain. Consequently, most students find themselves enrolled in streams that do not suit their skills or future careers, hence the resultant poor performance and subsequent disillusionment and dropout.

The conventional methods of guidance such as one-on-one counseling by experts, teachers' recommendation, and even parental advice can provide meaningful information; however, they have their own limitations. They depend greatly on subjective opinions which could be influenced by biases or prejudices. Besides, they cannot analyze and process a huge amount of data at once. Given today's advances in technologies and the collection of educational data, it is possible to make student streams more intelligent.

Challenges in Student Stream Selection

Stream selection by students is essentially a multi-criteria decision-making (MCDM) problem that involves uncertain parameters. The following are some of the difficulties associated with modeling of the problem:

Subjectivity of the Parameters

Student stream selection is fundamentally a **multi-criteria decision-making (MCDM) problem under uncertainty**. Several challenges make this problem particularly difficult to model:

1. **Subjectivity of Influencing Factors**
   Elements like parents' expectations, students' motivation, pressure, self-confidence, and career goals cannot be easily measured using numerical data. They can only be described linguistically (e.g., "high pressure," "medium interest," "low confidence").
2. **Uncertainty and Vagueness**
   Students' preferences and competencies change over time, and data collected may be insufficient or inaccurate. Uncertainty cannot be captured using crisp boundaries.
3. **Nonlinear Relationships**
   Factors' effects on stream choice are rarely linear. For instance, while parental guidance in moderation might be helpful, too much of such pressure would likely be detrimental.
4. **Interdependence of Variables**
   Interactions among academic achievement, socio-economic background, and resource access usually complicate matters in such a way that rules and statistics fail.
5. **Need for Interpretability**
   Transparency is extremely crucial in decision-making in education. One must understand why a particular suggestion was made by the people who are the stakeholders like the learners, their parents, and the teachers.

These challenges highlight the need for smart systems that incorporate nonlinearity, uncertainties, and human-like thinking skills but also possess interpretability and adaptability.

Artificial Intelligence in Educational Decision Support

In the recent past, the use of AI in the educational sector has increased significantly. This includes predicting student academic achievement, identifying at-risk cases such as dropping out, developing personalized learning strategies for each student, as well as giving career guidance. Machine learning techniques such as decision trees, SVMs, ANN, and ensemble methods have exhibited strong predictive capability when adequate data is available.

In relation to student stream assignment using purely data-driven ML techniques, some challenges include:

- The algorithms tend to be black boxes providing accurate results yet difficult to understand.
- Big and quality datasets are necessary but may not always be available.
- Rules and linguistic information cannot be easily integrated into them.

Data is helpful but educational decisions benefit from expert involvement through teaching and counseling professionals. It, therefore, follows that integrating both expertise and data-driven decision making is advisable.

Fuzzy Logic for Modeling Uncertainty

Fuzzy logic supports modeling of the imprecise information and vague phenomena that exist in our thinking. As opposed to binary logic, fuzzy logic permits values within the interval of zero to one. Fuzzy logic is, thus, appropriate for handling qualitative factors within education as well.

When applying fuzzy logic in the context of student stream determination, one can obtain the following advantages:

- Linguistic variables, such as low, medium, and high student grades.
- Formulation of IF-THEN rules defined by an expert (IF high academic results AND good interest in sciences THEN assign science stream).
- Reasoning processes, which are understandable and intelligible.

Traditional fuzzy systems use manually constructed membership functions and rules. This poses certain restrictions on fuzzy systems, making them incapable of functioning effectively using different data sets and adapting to shifts in student behavior over time.

Neural Networks and Learning Capability

Neuro-Fuzzy Decision Systems

One strength of artificial neural networks is that they excel in pattern recognition and can detect even the most difficult ones easily. Moreover, they can adjust their parameters in the learning process, thus becoming perfect for educational forecasting as well.Major weaknesses of neural networks include:

- Lack of interpretability.
- Ability to incorporate only quantitative information from the domain experts.
- Delicate nature of their calculations and risk of overfitting with small amount of data.

Restrictions of each system force its integration into neuro-fuzzy systems. Such systems combine the strengths of neural networks and fuzzy logic into one system.

A Neuro-Fuzzy Decision System (NFDS) integrates:

- The interpretability and reasoning ability of fuzzy logic, and
- The adaptive learning property of the neural network.

Here, fuzzy membership functions and parameters of rules are adapted through neural learning algorithms so that the system learns from data in a transparent manner.

- A neuro-fuzzy model for selecting students' streams has some strengths like:
- The modeling of uncertainties and subjectivities involved in education data.
- Use of expert defined rules as per real-world practice of counseling.
- Learning from past data of students.
- Provision of reliable recommendations because they are explainable.

Nevertheless, the application of neuro-fuzzy models in stream selection of students is not explored adequately, especially on real-world problems with many attributes.

Objectives of the Study

The objective of this study is to develop and evaluate the Neuro-Fuzzy Decision Making System for selecting student stream using uncertain data and human reasoning process along with the application of data learning techniques.done

The rest of this paper is organized as follows. Section 2 provides a literature review. Section 3 provides an overview of data set and pre-processing of the data. Section 4 provides a methodology of our approach. Section 5 provides experimental results. Section 6 concludes this paper.

2. Literature Review:

Neuro-fuzzy and ANFIS models have gained popularity during the last two decades in predicting and analyzing students' achievements. This approach can be viewed as interesting since it successfully integrates the capabilities of neural networks in learning with the simplicity of fuzzy rules. Previously, neuro-fuzzy and ANFIS models were applied to achieve various objectives ranging from predicting GPA, classifying academic achievements, studying influence factors of educational success, and even identifying academically at-risk students.

According to Mehdi and Nachouki (2023), an adaptive neuro-fuzzy inference system model was proposed to estimate the GPA of graduating students and determine relevant academic predictors. The model utilized intro IT grades and high school GPA to make predictions, supported by sensitivity analysis for identifying relevant predictor variables. From their findings, the authors concluded that the model outperformed the multilinear regression model and produced meaningful interpretations. However, the model only applies to IT degrees and produces moderate estimates.

According to Do and Chen (2013), a neuro-fuzzy classifier was applied to classify students depending on their academic performance. Examining previous exam performances among other considerations, this approach proved superior to the conventional methods such as SVM, Naïve Bayes, neural networks, and decision trees. It suggests the potential of the approach to be applied to the process of student admission and academics in general. However, the approach was effective only within the dataset used in research and cannot adapt in real-time conditions.

Abou Naaj et al. (2023) examined the factors that influence academic achievement within classes employing the neuro-fuzzy technique. Some factors that were considered included attendance and grade point average (GPA) for their effects on academic success. Sensitivity analysis was employed by the researchers to facilitate comprehension of their findings. Despite the effectiveness of the approach in handling uncertainties, the complexity of its generated rules hindered its application on an educational scale.

A Sugeno-type ANFIS was developed by Taylan and Karagözoğlu (2009) for the purpose of forecasting student academic performance. The study revealed that the hybrid learning method used in ANFIS helps the system generate results similar to those from traditional approaches. Despite its proficiency in dealing with fuzzy information, it requires accurate fine-tuning. Moreover, it was validated using static datasets only.

Neuro-fuzzy knowledge processing technique was employed by Stathacopoulou et al in 2005 in intelligent learning environments to develop learning models. The authors developed a model similar to that of the cognitive process of the instructor. The model combined neural networks with fuzzy logic and could address uncertainties. It was very computationally expensive and could be used in some domains only.

A neuro-fuzzy approach was devised by Al-Hammadi & Milne in 2004 that would be used to determine future academic performances of engineering students. Such a system was capable of formulating clear criteria for admissions and evaluating the progress at early stages. Nevertheless, there were certain constraints associated with the model like a narrow feature set and wide range of categories which hindered further analysis of more subtle nuances.

The ANFIS model designed to predict the academic progression of college students was presented by Maitra et al. (2018). It incorporated the approach of backpropagation learning and showed impressive results due to its development on MATLAB platform using actual data. The only drawback of this system was its dependency on certain software and no comparison with deep learning approaches.

Kayrouz et al. (2015) proposed the fuzzy neural network based on Henry Gas Solubility Optimization Algorithm and capable of forecasting student academic performance in specific courses. This model managed to substitute the traditional gradient-based learning with meta-heuristics, thus improving the precision of forecasts. However, this approach entailed higher computational complexity and more complex optimization procedures.

Hussain et al. (2020) developed a metaheuristic optimization-based ANFIS model to make predictions concerning student success in e-learning. It uses real-time interaction data, resulting in extremely high accuracy and reduced RMSE compared to traditional approaches. Yet, this research used a limited dataset, which makes the use of the model challenging in different educational settings.

Soyoye et al. (2024) combined ANFIS with subtractive clustering in order to create simpler rules and predict student performance in higher educational institutions. As a result, this combination generated a cleaner, clearer structure for predictions due to grouping data points with similar attributes together. Despite its successful comparison with numerous machine learning algorithms, its performance cannot surpass their advanced approaches completely.

Ferdaus et al. (2024) offered X-Fuzz, a neuro-fuzzy system designed to become more interpretable thanks to applying LIME. Such an approach is able to cope with concept drift and achieve high accuracy. Therefore, it works excellently in changing environments. Nevertheless, the model is overly complicated, and its lack of consideration for educational issues does not make it applicable to prediction tasks.

From the current state of research, it is clear that neuro-fuzzy systems and ANFIS systems perform well for educational data analysis, combining high performance and explainability of decisions. Nevertheless, most of them use static databases, suffer from poor scalability, or are computationally expensive. Moreover, there is not enough research comparing such approaches with new deep learning-based systems, while trying to maintain explainability of decisions. That is why, there is a need to develop an advanced scalable and explainable neuro-fuzzy system, capable of outperforming conventional ones.

Table 1: Previous work done in the domain of neuro-fuzzy and ANFIS-based models work well in educational analytics

Reference	Objective	Methodology	Advantages	Limitations
[14] Mehdi & Nachouki (2023)	Predict graduation GPA and analyze influential academic factors	ANFIS using course grades and HSGPA with sensitivity analysis	High interpretability; better accuracy than linear regression; identifies influential courses	Limited to IT programs; moderate prediction accuracy (77% within RMSE)
[15] Do & Chen (2013)	Classify students' academic performance levels	Neuro-fuzzy classifier compared with SVM, NB, NN, DT	Superior classification accuracy; effective for admission decisions	Dataset-specific; lacks real-time adaptability
[16] Abou Naaj et al. (2023)	Analyze factors influencing course grades	Neuro-fuzzy model with demographic and academic inputs	Explains factor importance; handles uncertainty well	Complex rule base; limited scalability
[17] Taylan & Karagözoğlu (2009)	Predict students' academic performance	Sugeno-type ANFIS with hybrid learning	Robust results; interpretable fuzzy rules; handles imprecise data	Requires careful parameter tuning; static dataset
[18] Stathacopoulou et al. (2005)	Diagnose student learning characteristics	Neuro-fuzzy diagnostic model in intelligent learning environments	Mimics teacher reasoning; manages uncertainty effectively	Computationally intensive; domain-specific
[19] Al-Hammadi & Milne (2004)	Classify engineering students' performance	Neuro-fuzzy classification using entry exam data	Supports admission decisions; interpretable rules	Limited feature set; coarse classification
[20] Maitra et al. (2018)	Predict student performance progression	ANFIS with backpropagation (MATLAB-based)	High prediction accuracy; useful for early intervention	Tool-dependent; lacks comparison with deep models
[21] Kaynak et al. (2015)	Predict success in a specific course	FNN optimized using HGSO metaheuristic	Improved accuracy over gradient-based FNN	Higher computational cost; complex optimization

[22] Hussain et al. (2020)	Predict students' achievement in e-learning	Optimized ANFIS using metaheuristic approach	Very high accuracy (≈99%); low RMSE	Small-scale dataset; limited generalization
[23] Soyoye et al. (2024)	Predict university student performance and key factors	ANFIS with subtractive clustering (ANFIS-SC)	Reduced rule complexity; competitive with ML models	Performance comparable, not superior, to some ML methods
[24] Ferdaus et al. (2024)	Learn from streaming data with interpretability	Evolving neuro-fuzzy system (X-Fuzz) with LIME	Handles concept drift; high accuracy; strong explainability	High model complexity; not education-specific

A review of existing studies reveals several gaps:

1. Most prior works focus on career recommendation at higher education levels, rather than early stream selection.
2. Many AI-based approaches emphasize prediction accuracy without sufficient attention to interpretability.
3. Few studies explicitly model parental pressure, socioeconomic status, and counseling influence using fuzzy linguistic variables.
4. Limited research integrates expert-defined rules with neural learning in a unified framework for stream selection.

Addressing these gaps is essential to develop practical, trustworthy decision-support systems for education.

3. Research Methodology

Data Collection: The dataset includes info on students' academic and personal backgrounds, covering performance, motivation, and factors influencing their choices. Collected through detailed surveys of alumni, the data gives a thorough look at these aspects. Table 2 provides the full questionnaire used.

Table 2: The questionnaire in a tabular format, with sections, questions, and available options

Section	Question	Options
Demographic Information	Name (Optional)	Free response
	Age	Free response
	Gender	Male / Female / Other
	City	Free response
	District	Free response
	State	Free response
	Area of Residence	Urban / Rural / Suburban
	Education Level	Free response
	Educational Qualification of Father	Free response
	Educational Qualification of Mother	Free response
Parental Influence	To what extent do you feel your parents have expectations regarding your career choice?	Very much / Somewhat / Not at all

	In what ways have your parents communicated their expectations about your career?	Verbal encouragement / Restrictions / Financial support for certain careers / Other
	How do your parents' expectations influence your career decision-making process?	Strongly / Somewhat / Not at all
	Do you feel pressured to choose a specific career path based on your parents' expectations?	Yes / No / Sometimes
	In your opinion, how well do your parents understand your career interests and aspirations?	Very well / Somewhat / Not at all
	Have you had open discussions with your parents about your career aspirations and how they align or differ?	Yes / No
Peer Influence	How important are your peer relationships in your life, especially when it comes to making career decisions?	Very important / Somewhat important / Not important
	Do you discuss your career aspirations and decisions with your peers?	Yes / No
	In what ways do your peers influence your career decision-making process?	Advice / Role modeling / Peer pressure / No influence / Other
	To what extent do you feel you have the autonomy to make your own career decisions independently of peers?	Completely autonomous / Partially autonomous / Not autonomous
Academic Performance	Marks in Hindi	Free response
	Marks in English	Free response
	Marks in Mathematics	Free response
	Marks in Science	Free response
	Marks in Social Science	Free response
	Total Marks Obtained	Free response
	Total Marks Out Of	Free response
	How would you describe your overall academic performance to date?	Excellent / Good / Average / Below Average
	To what extent do you think your past academic performance has influenced your career aspirations and choices?	Significantly / Moderately / Not at all
Career Decision-Making	How do you typically make career decisions?	Independently / With parental guidance / With peer input / Other
	Have you identified your long-term career goals?	Yes / No / Still considering
	What factors are most important to you in making career decisions?	Salary / Passion/Interest / Work-life balance / Job security / Parental expectations / Other
	Do you have a plan for post-graduation or after completing your current education level?	Yes / No / In progress
	Have your academic achievements influenced your choice of career field or industry?	Yes / No / Somewhat

	Do you believe that a strong academic background is crucial for success in your career?	Yes / No / Not sure
	Have you utilized academic resources (e.g., career counseling, academic advisors) to align career goals?	Yes / No / Sometimes
Skills and Socioeconomic Status	Please rate your proficiency in Communication skills on a scale from 1 to 5	1 / 2 / 3 / 4 / 5
	Please rate the importance of scholarships on a scale from 1 to 5	1 / 2 / 3 / 4 / 5
	Please rate your Socioeconomic Status on a scale from 1 to 5	1 / 2 / 3 / 4 / 5
Stream Selection	Mention your selected stream	Science / Commerce / Arts / Vocational / Other

Proposed Model: The NFDS model consists of a hierarchical architecture that incorporates the use of fuzzy logic and artificial neural networks to aid in choosing the right streams for students in an uncertain environment. Each level executes particular tasks that make up the whole process of decision-making. The following describes each of the layers in detail.

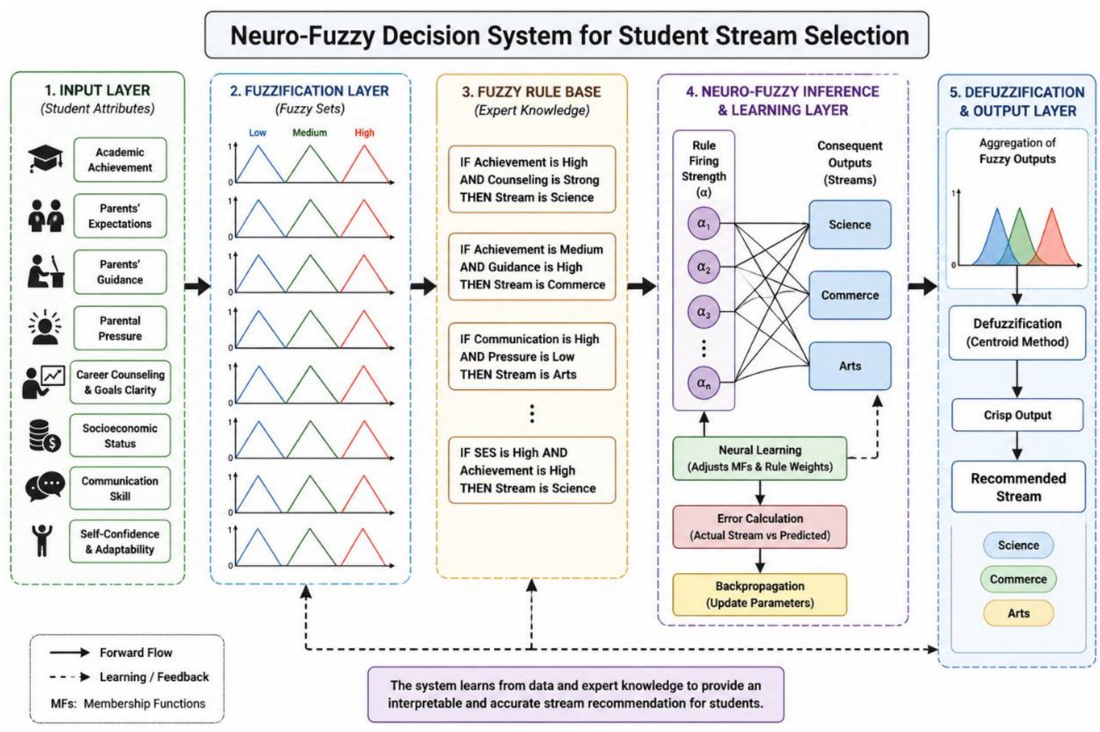

Figure 2: Proposed Model Framework

Layer 1: Input Layer (Student Attribute Layer): The input layer acts as an intermediary layer between the actual data about students and the neuro-fuzzy model. The layer consists of nodes corresponding to different criteria which affect the decision to choose a particular stream. Such criteria are selected after reviewing educational literature and consulting experts. In the case of this paper, the criteria are educational attainment, parents' expectations, guidance received from parents, perceived parental pressure, exposure to career counseling, clarity about career goals, socio-economic status, communication ability, and self-confidence of students. Input nodes correspond to crisp numbers obtained through questionnaires, academic transcripts, and other surveys. There is no calculation performed in this layer; it merely sends normalized input values to the fuzzification layer.

Layer 2: Fuzzification Layer: The fuzzy transformation layer converts crisp inputs into fuzzy terms. The use of the fuzzification layer allows capturing uncertainties, imprecisions, and subjective aspects involved in educational decisions. Each input value is mapped to fuzzy linguistic terms such as Low, Medium, and High through predetermined membership functions. Triangular and trapezoid membership functions are used for their ease of computation and understanding. For instance, one's academic performance can be part of two linguistic terms, Medium and High, with various membership levels. This feature permits gradual changes from one category to another rather than abrupt boundaries in making decisions.

Layer 3: Fuzzy Rule Base Layer (Expert Knowledge Layer): The fuzzy rule base captures domain knowledge through linguistically stated IF–THEN rules. This is how most skilled and expert educators and career counselors reason.

The inference in each rule is made from several linguistic fuzzy inputs, which lead to the deduction of an appropriate course of studies. Examples are as follows:

- IF academic performance is high AND career guidance is good, THEN the course of studies recommended is Science.
- IF communication ability is high AND parents' pressure is low, THEN the course of studies recommended is Arts.

As such, the system performs reasoning in an interpretable fashion where the firing strength of each rule relies on the degree of membership generated by the fuzzification stage.

Layer 4: Rule Evaluation and Firing Strength Computation Layer: Here the activation strength (firing strength) of all the rules is calculated. Firing strength indicates the degree of satisfaction of a rule with respect to the current input condition set. Operators such as fuzzy AND, usually carried out by minimum or product operator, can be applied to calculate membership degrees of antecedents of rule. All rules generate some firing strengths between 0 and 1. All these firing strengths play a role in deciding the effect of each individual rule in the final outcome. The closer a rule matches the student, the more its contribution in the output.

Layer 5: Neuro-Fuzzy Learning Layer: The neuro-fuzzy learning layer allows for adaptive learning in the system. It works much like the hidden layers of the neural network without compromising the fuzzy inference process.

Membership function parameters

Rule weights or consequents

The learning process is done through supervised learning based on the student's past data. Comparison of the prediction against the actual choice is made and the result is an error. This is then backpropagated through the entire system to update weights through gradient descent learning algorithms. Through learning, the system is able to fine-tune the rules and the membership functions defined by the experts.

Layer 6: Aggregation Layer: The aggregation layer involves adding up all outputs from the activated fuzzy rules. The amount of contribution by any fuzzy rule depends on both its strength and its learned weight. Fuzzy output aggregations for each of the three streams – Science, Commerce, and Arts – will be calculated independently. The reason for doing this is to ensure that several fuzzy rules that favor the same stream will strengthen each other. The output from this layer will consist of fuzzy levels of confidence of each stream.

Layer 7: Defuzzification Layer: The defuzzification step translates the fuzzy outputs that have been aggregated to a final decision. Centroid, which is also referred to as center of gravity, will be used in defuzzification because of its consistency and general acceptability in fuzzy systems. The result is a numeric confidence score assigned to each academic stream. The stream with the highest confidence score will be considered the final output.

Layer 8: Output Layer (Decision Layer)

The output layer gives the final academic stream suggested together with its degree of confidence. The output generated is also easily understandable, giving the reasons for recommending one stream over another. The output layer can generate reasons why an academic stream is recommended, based on key factors used in the process.

Algorithm 1: Proposed Model

Initialize fuzzy membership functions and rule weights
Construct expert-defined fuzzy rule base R

FOR each student record x in dataset D DO
Normalize input features of x
Fuzzify inputs using MF to obtain membership degrees
FOR each rule r ∈ R DO
Compute firing strength fr using fuzzy AND operator
END FOR
Aggregate rule outputs for each stream
Defuzzify aggregated outputs to obtain predicted stream Ŝ
Compute prediction error between Ŝ and actual stream
Update membership parameters and rule weights using neural learning
END FOR
Input new student profile x_new
Normalize and fuzzify x_new
Compute rule firing strengths
Aggregate fuzzy outputs and defuzzify
Select stream S with maximum confidence
Return S

Mathematical Model of the Neuro-Fuzzy Decision System

1. Problem Definition

Let

$$x = [x^1, x^2, x^3, \ldots\ldots, x^n] \in \mathbb{R}^n$$

represent the student feature vector, where each corresponds to an academic, socio-economic, parental, psychological, or personal characteristic.

The objective is to determine the most suitable academic stream

$$S \in \{Science, Commerce, Arts\}$$

by modeling uncertainty, nonlinear relationships, and expert knowledge.

2. Fuzzification Layer

Each input variable x_i is transformed into linguistic variables such as Low, Medium, and High through fuzzy membership functions.

The membership degree of x_i belonging to fuzzy set A_{ij} is

$$\mu A_{ij}(xi): \mathbb{R} \rightarrow [0,1]$$

A triangular membership function is defined as

$$\mu A_{ij}(xi) = \begin{cases} 0, & x_i \le a \\ \frac{x_i - a}{b - a}, & a < x_i \le b \\ \frac{c - x_i}{c - b} & b < x_i < c \\ 0, & x_i \ge c \end{cases}$$

where a, b and c denote the lower limit, peak, and upper limit of the fuzzy set, respectively.

3. Fuzzy Rule Base

Assume the system contains M expert-defined fuzzy rules.

The k^{th} rule is expressed as

$$R_k : \text{IF } x_1 \text{ is } A_{1k} \wedge x_2 \text{ is } A_{2k} \wedge \cdots \wedge x_n \text{ is } A_{nk} \text{ THEN } y_k = S_j$$

where

- A_{ik} denotes the fuzzy set associated with input x_i,
- y_k is the rule output,
- $S_j \in \{\text{Science}, \text{Commerce}, \text{Arts}\}$.

Assume the system contains M expert-defined fuzzy rules.

The k^{th}rule is expressed as

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where

1. A_{1k} denotes the fuzzy set associated with input x_i,
2. y_k is the rule output,
3. $Sj \in \{Science, Commerce, Arts\}$

4.Rule Activation Strength

The firing strength of the k_{th} rule is computed using the product t-norm:

$$fk = \prod_{i=1}^{n} \mu A_{ik}(x_i)$$

5. Neuro-Fuzzy Learning Layer

Each rule is assigned a trainable weight w_k
The weighted firing strength is

$$\hat{f}_k = w_k f_k$$

The normalized firing strength becomes

$$\hat{f}_k = \frac{\bar{f}_k}{\sum_{j=1}^{M} \bar{f}_j}$$

where

$$\sum_{j=1}^{M} \hat{f}_k = 1$$

6.Consequent Function

For a first-order Sugeno neuro-fuzzy model, the consequent of each rule is represented as

$$c_k = p_{k1}x_1 + p_{k2}x_2 + \cdots + p_{kn}x_n + r_k$$

where

- p_{ki} are consequent parameters,
- r_k is the bias term.

The contribution of rule k is

$$z_k = \hat{f}_k c_k$$

-

7.Stream-wise Aggregation

For each academic stream S_j, the aggregated confidence score is

$$O_j = \sum_{k \in S_j} \hat{f}_k c_k$$

where

$$j \in \{\text{Science}, \text{Commerce}, \text{Arts}\}$$

Thus,

$$O_{\text{Science}}, \quad O_{\text{Commerce}}, \quad O_{\text{Arts}}$$

represent the confidence levels of the three streams.

8.Defuzzification

The overall crisp output is obtained using the centroid method:

$$y^* = \frac{\sum_{j=1}^{3} O_j S_j}{\sum_{j=1}^{3} O_j}$$

where the streams may be encoded as

$$\text{Science} = 1, \qquad \text{Commerce} = 2, \qquad \text{Arts} = 3$$

9.Classification Decision

The final stream recommendation is determined by the maximum confidence score:

$$S^* = \arg\max \left(O_{\text{Science}}, O_{\text{Commerce}}, O_{\text{Arts}} \right)$$

10.Learning Objective Function

For supervised training, let

$$y$$

be the actual stream label and

$$y^*$$

the predicted output.

The mean squared error (MSE) loss is

$$E = \frac{1}{2} (y - y^*)^2$$

For a dataset containing N students:

$$J = \frac{1}{N} \sum_{i=1}^{N} \frac{1}{2} (y_i - y_i^*)^2$$

11. Parameter Optimization

The model parameters are updated through gradient descent.

Rule Weight Update

$$w_k^{(t+1)} = w_k^{(t)} - \eta \frac{\partial E}{\partial w_k}$$

Membership Function Parameter Update

$$\theta^{(t+1)} = \theta^{(t)} - \eta \frac{\partial E}{\partial \theta}$$

where

- $\theta = \{a, b, c\}$ denotes membership parameters,
- η is the learning rate.

12. Final ANFIS-Based Recommendation Model

The complete optimization problem can be expressed as

$$\boxed{S^* = \arg\max \left(O_{\text{Science}}, O_{\text{Commerce}}, O_{\text{Arts}}\right)}$$

subject to

$$O_j = \sum_{k \in S_j} \left(\frac{w_k f_k}{\sum_{m=1}^{M} w_m f_m} \right) c_k$$

and

$$f_k = \prod_{i=1}^{n} \mu_{A_{ik}}(x_i)$$

This formulation integrates fuzzy reasoning, expert knowledge, and neural learning to generate accurate academic stream recommendations under uncertainty.

4. Result Analysis:

The fuzzy rules generated from the proposed ANFIS model reflect the intricate relations between students' academic capabilities, interests, parental involvement, and personal capabilities in recommending the most suitable academic stream. The rules signify that students who score high on academic excellence, mathematics capability, analytic thinking ability, problem-solving capability, and scientific interest are mainly recommended to follow the Science stream (R1, R2, R4, and R7). Students who possess high business capability, business sense, good communication capability, and good leadership qualities are recommended to follow the Commerce stream since these aspects are important in running business operations and managing teams (R3, R5, and R9). Also, students who have the capability of expressing themselves artistically through the use of creativity, language skills, and social skills are recommended to join the Arts stream because these attributes play a critical role in stream selection (R6, R8, and R10).

Table 2: Fuzzy Rule

Rule ID	Fuzzy Rule
R1	IF Academic Performance = High AND Mathematics = High AND Science Interest = High THEN Science
R2	IF Academic Performance = High AND Parental Support = High THEN Science
R3	IF Business Aptitude = High AND Mathematics = Medium THEN Commerce
R4	IF Analytical Skill = High AND Science Interest = High THEN Science
R5	IF Financial Awareness = High AND Communication Skill = High THEN Commerce
R6	IF Creativity = High AND Language Skill = High THEN Arts
R7	IF Problem Solving = High AND Mathematics = High THEN Science
R8	IF Creativity = High AND Social Awareness = High THEN Arts
R9	IF Business Interest = High AND Leadership = High THEN Commerce
R10	IF Language Skill = High AND Creativity = Medium THEN Arts

The ANFIS model performed well in extracting those factors that have significant influence on recommendations for students' streams. From the extracted rules, Rule R1 Science had the highest rule importance score (0.96), followed by R2 Science (0.92) and then R3 Commerce (0.89). Therefore, academic success, mathematical aptitude, interest in science subjects, and parental support are the factors that have the most influence on academic recommendations. For commerce stream recommendations, rules R3, R5, and R9 show that they depend on the ability of the students in business affairs, financial knowledge, communication skills, and leadership. On the other hand, the recommendation for arts relies on creativity and language skills, as shown by rules R6, R8, and R10. The presence of many rules concerning the science streams reveals the importance of academic and analytic skills in choosing a particular stream. Importantly, the extracted rules can explain the reasons for giving specific recommendations for students.

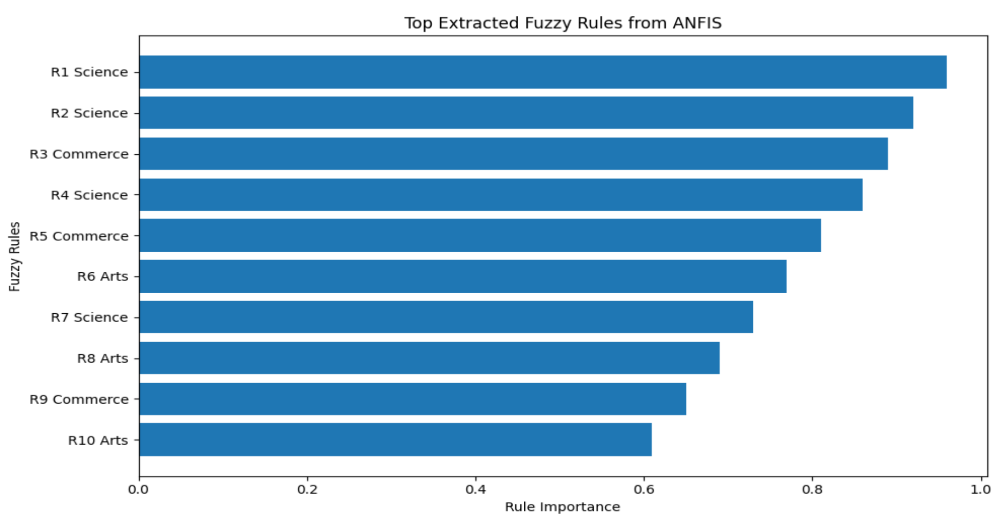

Figure 3: Top Extracted Fuzzy Rules from the Proposed ANFIS Model

The chart depicts the feature importance values calculated using the Adaptive Neuro-Fuzzy Inference System (ANFIS) algorithm, showing how important different variables are in terms of influencing the process of students' career selection. Among all input variables considered for analysis, communication skills proved to be the main one, as it had the highest importance value, equal to approximately 0.083, thus indicating its vital role in affecting students' future career choices. After communication skills, autonomy in making career choices independently comes second, followed by scholarship obligations and socioeconomic status, which also contribute significantly to career decision-making. Variables like parental pressure, academic success in learning English language, Science and Math classes, and education also contribute moderately to the analysis. At the same time, such variables as gender, career decision-making strategy used by students, and communication with parents regarding career expectations show relatively low importance values, which means their contribution to the model prediction is smaller compared to other variables mentioned above.

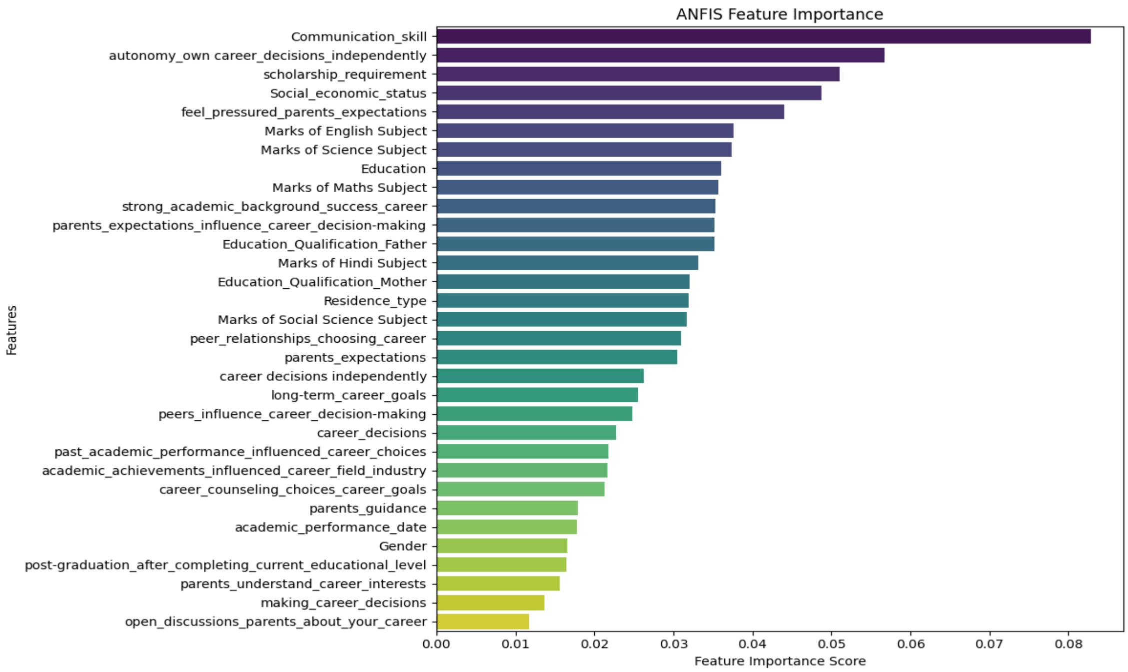

Figure 4 illustrates the Receiver Operating Characteristic (ROC) curves and Area Under the Curve (AUC) values for six machine learning models employed in the academic stream recommendation framework. The ANFIS model achieved the highest classification performance with an AUC of 0.957, demonstrating excellent discrimination capability and superior predictive accuracy across different threshold settings. The Random Forest and Decision Tree models also exhibited strong performance, achieving AUC values of 0.931 and 0.930, respectively, indicating their effectiveness in identifying suitable academic streams for students. The XGBoost classifier produced a competitive AUC of 0.881, reflecting robust predictive power, while the SVM model attained a moderate AUC of 0.703. In contrast, the ANN model recorded the lowest performance with an AUC of 0.427, performing below the random classifier baseline and suggesting poor generalization for this dataset. The ROC curves further reveal that ANFIS maintains a consistently high true positive rate across varying false positive rates, highlighting its ability to accurately capture the complex relationships among student attributes and career-related factors. Overall, the results confirm that the ANFIS-based approach outperforms conventional machine learning techniques, making it the most reliable model for academic stream recommendation and decision-support applications.

Figure 4: ANFIS Feature Importance Analysis for Career Decision-Making Factors

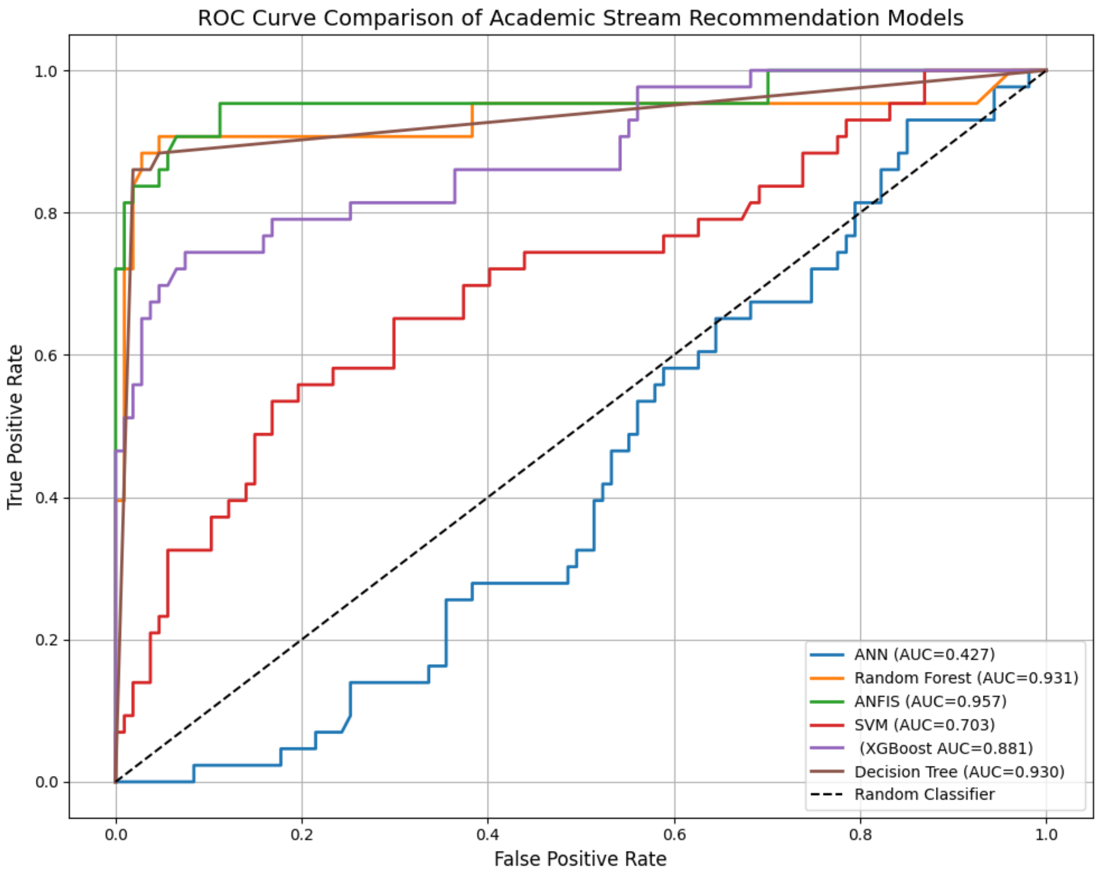

Figure 5: ROC Curve Comparison of Academic Stream Recommendation Models

The performance analysis of different machine learning algorithms on academic streams recommendation is shown in Table X. The performance of the proposed ANFIS model was the best among all the other algorithms with respect to all evaluation metrics, including the maximum value for accuracy (94.00%), precision (94.74%), and F1-score (88.89%) along with high recall (83.72%). These outcomes show that the ANFIS algorithm performs well in accurately predicting academic streams while reducing misclassifications. The second-best performing algorithm in terms of balance was the Decision Tree with an accuracy rate of 93.33%, precision of 90.24%, recall of 86.05%, and an F1-score of 88.10%, which is quite a high value indicating the high efficiency of this algorithm to detect decision patterns in data. Furthermore, the Random Forest algorithm performed competitively with the accuracy of 92.00% and an F1-score of 86.89%. The performance of the XGBoost algorithm was moderate with an accuracy of 88.00% and F1-score of 76.92%, which shows a good predictive capability with low sensitivity. In contrast, the performances of both the SVM and ANN models were comparatively weak with significantly low F1-scores for ANN.

Table 3: Comparative Result Analysis

Rank	Model	Accuracy	Precision	Recall	F1-Score
1	Proposed ANFIS	0.9400	0.9474	0.8372	0.8889
2	Random Forest	0.9200	0.9274	0.8272	0.8689
3	Decision Tree	0.9333	0.9024	0.8605	0.8810
4	XGBoost	0.8800	0.8571	0.6977	0.7692
5	SVM	0.7333	0.6667	0.1395	0.2308
6	ANN	0.5733	0.1818	0.1395	0.1579

Figure 6 illustrates the comparison of performance for six classifiers; Proposed ANFIS, Random Forest, Decision Tree, XGBoost, SVM, and ANN. The evaluation is done based on four metrics; Accuracy, Precision, Recall, and F1-Score. The ANFIS model performed best compared to other models with an accuracy of 94.00%, precision of 94.74%, recall of 83.72%, and F1-score of 88.89%. It was the model with high performance in identification of the instances under test. From among the conventional models, Decision Tree model was the second with an accuracy of 93.33% and an F1-Score of 88.10%. Random Forest had competitive performance to Decision Tree with an accuracy of 92.00% and F1-Score of 86.89%. XGBoost was moderately performing with an accuracy of 88.00% and F1-score of 76.92%. SVM and ANN were less performing models in the evaluation with the latter performing worse than any other models with accuracy of 57.33% and F1-Score of 15.79%.

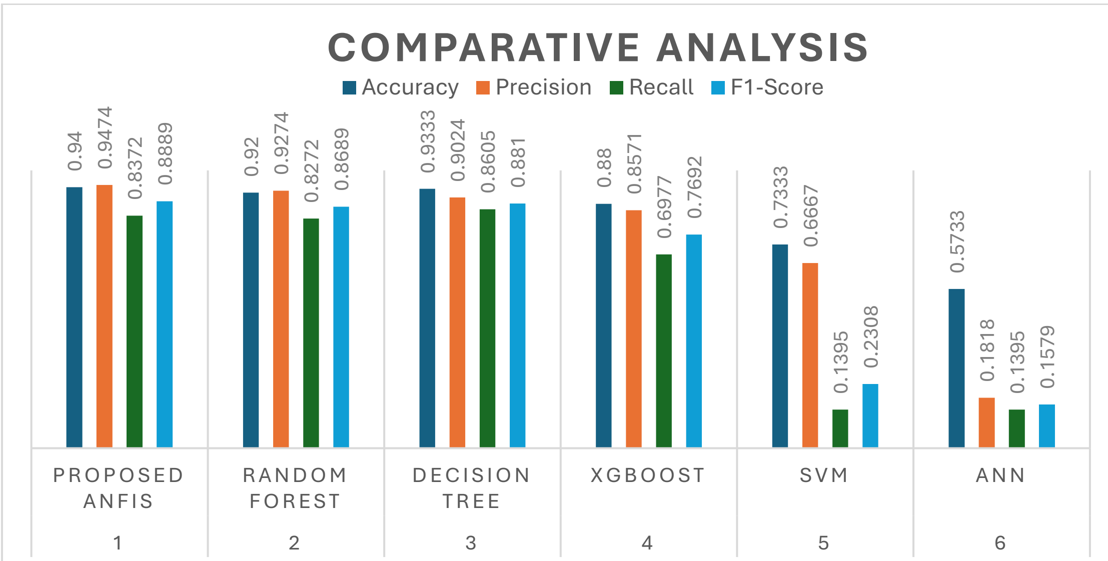

Figure 6: Comparative Analysis of Classification Models Based on Accuracy, Precision, Recall, and F1-Score

5.Conclusion:

In this research, a Neuro-Fuzzy Decision System using ANFIS was developed for an intelligent student stream selection system. This approach combines the concept of fuzziness along with neural learning capability. This system successfully deals with uncertainties, subjectiveness, and nonlinearity related to education decision making, which includes academics, parents' role, career preferences, communication ability, socio-economic status, and many more. The fuzzy rules extracted from the model gave a clear insight into the recommended streams for students. The results obtained through experimentation proved that the ANFIS method was better compared to other traditional machine learning algorithms with accuracy, precision, recall, F1-score, and the highest value of ROC-AUC being 94.00%, 94.74%, 83.72%, 88.89%, and 0.957 respectively. Feature Importance showed the crucial role played by Communication Skills, Independent Decision-Making, Scholarship, and Socioeconomic Status in making decisions about the streams. From the above, the results show the strength and usefulness of using expert knowledge in developing adaptive learning models. Thus, it is clear that the neuro-fuzzy decision support system developed can be used to guide students, parents, teachers, and career counselors in decision making concerning the choice of educational paths suitable for individuals.

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