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Cognitive Linguistic Corpus Classification and Terminology Database Design Based on Multimedia Technology

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Abstract: - With the continuous development of the social economy, multimedia has been valued more and more as a computer technology with strong professional technology and high application level. The quality of multimedia professionals is predicted and analyzed for multimedia professional talent through the Internet according to a Chinese keyword extraction algorithm. It realizes the extraction of keywords through Internet intelligence information acquisition for solving the problem of Internet information explosion, aiming to solve the talent quality prediction analysis. The prediction and analysis of multimedia professional talent quality play a crucial role in talent recruitment and development in the ever-evolving multimedia industry. This paper constructed a Fuzzy Secured Hybrid Search (FSHS) for keyword extraction in the Chinese Language. The proposed FSHS model computes the features in the text for the computation of the talent quality prediction for the extraction of the keywords. Through the utilization of the fuzzy logic model, the features in the text are computed and classification is performed classification and extraction of the features. The simulation results show that the Chinese keyword extraction algorithm has a high recall rate and precision rate, and can effectively predict the quality of professional talents.

Keywords: Multimedia, Keyword Extraction, Fuzzy hybrid Search, Feature Extraction, Classification, Chinese language

I. INTRODUCTION

Multimedia Professional Talent Quality Prediction Analysis is a cutting-edge and innovative approach designed to revolutionize the recruitment process within the multimedia industry [1]. With harnessing the power of advanced data analytics, artificial intelligence, and machine learning, this sophisticated system aims to accurately predict the quality and potential of multimedia professionals. From graphic designers to video editors, animators to audio engineers, the platform assesses a diverse range of talents and skills [2]. By analyzing a candidate's portfolio, past projects, technical expertise, and creative capabilities, the prediction analysis offers invaluable insights to employers seeking the most suitable and talented individuals for their multimedia projects [3]. Emphasizing efficiency and precision, this game-changing solution promises to streamline talent acquisition, enhance project outcomes, and elevate the multimedia industry to new heights.

Multimedia Professional Talent Quality Prediction Analysis is a comprehensive and data-driven approach that utilizes various algorithms and statistical models to assess the suitability and caliber of multimedia professionals [4]. This system takes advantage of vast amounts of data, including the candidates' portfolios, work history, educational background, skillsets, certifications, and even social media presence, to build a comprehensive profile for each individual [5]. The analysis starts with data preprocessing, where all the candidate information is cleansed, standardized, and transformed into a format that can be efficiently processed [6]. The system then leverages machine learning techniques such as supervised and unsupervised learning to identify patterns and trends within the data. Neural networks, decision trees, and clustering algorithms are commonly employed to recognize relevant patterns and characteristics of successful multimedia professionals [7]. One critical aspect of this prediction analysis is the inclusion of expert evaluations and human feedback. As the system learns from historical data and candidate performance, it becomes more refined and accurate over time. By integrating human insights and judgments, the model can adapt and align with real-world expectations and nuances of the multimedia industry [8].

Employers and hiring managers benefit significantly from this advanced analysis. They can gain valuable insights into a candidate's strengths, weaknesses, and areas of expertise [9]. This empowers them to make informed decisions, matching the right professionals with the specific requirements of their multimedia projects. Moreover, this predictive approach helps reduce bias in the hiring process, ensuring that candidates are assessed based on their actual skills and qualifications rather than subjective factors [10]. This contributes to a more inclusive and diverse workforce within the multimedia industry. As the multimedia landscape continuously evolves, this prediction analysis adapts alongside it. The system keeps track of emerging trends, new technologies, and evolving demands

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in multimedia production [11]. By doing so, it ensures that employers are presented with candidates who possess the latest and most relevant skill sets, keeping their projects at the forefront of innovation.

Multimedia Professional Talent Quality Prediction Analysis represents a groundbreaking solution that optimizes talent acquisition, enhances project outcomes, and facilitates the growth and success of the multimedia industry [12]. It combines the power of data analytics, artificial intelligence, and human expertise to bring about a new era of precision and efficiency in multimedia talent recruitment. Keyword extraction plays a crucial role in enhancing the depth and accuracy of the Multimedia Professional Talent Quality Prediction Analysis [13]. In the context of talent evaluation, keyword extraction involves the use of advanced natural language processing techniques to automatically identify and extract relevant keywords, phrases, and concepts from the textual data associated with a candidate's profile. The textual data can include a candidate's resume, cover letter, project descriptions, blog posts, social media content, and any other written material that provides insights into their professional background and expertise [14]. These texts are parsed and analyzed to identify and prioritize the most significant words and phrases that represent the candidate's skills, experience, and domain knowledge. Once the relevant keywords are extracted, they are cross-referenced with an extensive database of multimedia-related terms, industry-specific jargon, and emerging trends [15]. This enables the system to understand the context and relevance of the extracted keywords in the multimedia domain. For example, if a candidate's portfolio contains keywords like "motion graphics," "video editing," and "3D animation," the system recognizes their expertise in multimedia production [16].

With integrating keyword extraction into the talent prediction analysis, employers gain a more comprehensive and objective view of a candidate's capabilities [17]. It reduces the reliance on subjective evaluations and allows for a data-driven and evidence-based assessment. This not only streamlines the talent selection process but also ensures that employers are identifying candidates who possess the exact skills and qualifications needed for their specific multimedia projects [18]. Keyword extraction enables the system to stay up-to-date with the latest industry trends and technological advancements. As the multimedia landscape evolves, new keywords and concepts emerge, and the analysis adapts accordingly. This ensures that employers are presented with candidates who are well-versed in the latest multimedia tools, techniques, and creative approaches [19]. The use of keyword extraction in Multimedia Professional Talent Quality Prediction Analysis is a pivotal and sophisticated technique that further enhances the accuracy and depth of talent evaluation within the multimedia industry [20]. With employing natural language processing (NLP) algorithms, this innovative approach extracts and analyzes keywords from a candidate's portfolio, resume, and other relevant documents. These keywords are then cross-referenced with industry-specific terms and trends, providing invaluable insights into the candidate's expertise, strengths, and areas of specialization [21]. Through this process, the prediction analysis gains a comprehensive understanding of each professional's skill set, creative capabilities, and domain knowledge, enabling employers to make more informed and precise decisions in selecting the most suitable talents for their multimedia projects [22]. Ultimately, integrating keyword extraction into the analysis not only streamlines the talent assessment process but also ensures that employers identify and engage with multimedia professionals who possess the exact skills and qualifications demanded by the dynamic and ever-evolving multimedia landscape.

1.1 Contribution of the Paper

The paper makes several significant contributions to the field of talent prediction and analysis, particularly in the context of multimedia professionals. Some key contributions of the paper include:

1. The development and presentation of the FSHS algorithm itself is a major contribution. The FSHS algorithm combines fuzzy logic and feature extraction techniques to accurately extract relevant keywords from Chinese text data. This hybrid approach leverages the strengths of both fuzzy logic and feature extraction to enhance the accuracy and effectiveness of talent prediction and analysis.

2. The application of the FSHS algorithm to talent quality prediction in the multimedia industry is a valuable contribution. By effectively extracting keywords from Chinese text data related to multimedia professionals, the FSHS algorithm enables a more accurate and comprehensive assessment of talent quality. This enhancement can have a significant impact on the recruitment and evaluation processes in the multimedia domain.

3. The paper conducts a comparative analysis of the FSHS algorithm with Conventional Fuzzy and Artificial Neural Network (ANN) approaches. This analysis allows researchers and practitioners to gain insights into the

strengths and weaknesses of different keyword extraction methods. The comparison highlights the superior performance of the FSHS algorithm in precision and overall talent prediction.

4. Through extensive simulations and performance evaluations, the paper validates the effectiveness of the FSHS algorithm. By providing concrete numerical results and performance metrics, the study establishes the reliability and robustness of the FSHS algorithm in real-world scenarios.

5. The paper emphasizes the practical applications of the FSHS algorithm in talent management, multimedia education, and other related fields. The accurate talent quality prediction and keyword extraction capabilities of the FSHS algorithm make it a promising tool for enhancing talent assessment processes, aiding in career development, and supporting decision-making in various multimedia-related industries.

6. The paper contributes to the broader field of talent analytics by presenting an innovative and effective approach for talent quality prediction and analysis. The FSHS algorithm's application in talent assessment can potentially revolutionize how multimedia professionals are evaluated, identified, and selected for various roles, leading to more efficient and informed talent management practices.

II. RELATED WORKS

The integration of keyword extraction in Multimedia Professional Talent Quality Prediction Analysis brings greater efficiency, accuracy, and objectivity to the talent evaluation process. It empowers employers to make informed decisions and fosters a workforce that is well-equipped to meet the dynamic challenges of the multimedia industry. Sudha et al.'s [23] paper focuses on predicting personality traits through CV analysis using machine learning algorithms. This research is significant for the e-recruitment process as it suggests an automated approach to assess candidates' personalities based on their CVs. By using machine learning, employers can gain valuable insights into a candidate's personality characteristics, which may be useful in predicting job fit, team dynamics, and overall organizational compatibility.

Hanafizadeh et al. [24] investigate the consequences of social media usage on firm performance. The paper explores how social media activities may influence the performance of businesses. Understanding this relationship can help organizations tailor their social media strategies to enhance brand visibility, customer engagement, and overall business success. Långh et al. [25] study the quality of early intensive behavioral intervention as a predictor of children's outcomes. The research examines the impact of early intervention strategies on the development of children. The findings can inform educational and therapeutic interventions to improve outcomes for children with developmental challenges. Liu et al. [26] propose PQA-Net, a deep learning model for no-reference point cloud quality assessment. The paper introduces an innovative method to evaluate the quality of point cloud data without using reference data. This advancement can benefit various industries that rely on 3D data, such as virtual reality, augmented reality, and autonomous systems.

Pekkala and van Zoonen [27] examine the mediating role of social media communication self-efficacy in work-related social media use. The study investigates how employees' confidence in using social media for professional communication affects their actual usage. Understanding this relationship is vital for organizations seeking to leverage social media effectively for recruitment, networking, and branding purposes. Ahmed and Sheikh [28] explore the impact of information and communication technology skills on library and information science professionals. The paper investigates how these skills can enhance library services. It highlights the importance of technological proficiency in modern libraries and information management. Luo and Yang [29] propose a model for predicting and analyzing the quality of multimedia professional talents by combining multiobjective data and fuzzy evolution. The study aims to optimize talent selection in the multimedia industry. This model can help organizations identify and recruit multimedia professionals with the desired skills and expertise, leading to improved project outcomes and overall industry growth.

Wenzhi et al. [30] conduct a validity test of inter-judge agreement and behavioral prediction when using social media for talent selection. The paper examines the effectiveness of social media as a tool for talent assessment. The findings contribute to the ongoing discussions on the role of social media in talent acquisition processes. Shen [31] presents a study on AI-enabled talent training for cross-cultural news communication. The research explores the use of AI in developing talents for news communication in a cross-cultural context. This can be particularly valuable in today's globalized world where effective cross-cultural communication is crucial. Han and Wang [32] investigate the correlation among Chinese EFL teachers' self-efficacy, work engagement, and reflection. The paper explores the relationship between self-efficacy and other factors affecting English language teaching in China. The findings can guide educational institutions in supporting and enhancing teacher effectiveness and well-being. Tai et al. [33] study virtual reality's impact on car-detailing skill development, exploring learning outcomes predicted by VR self-efficacy, VR using anxiety, VR learning interest, and flow experience. Understanding these factors can help design effective VR-based training programs for skill development in various industries, leading to enhanced performance and proficiency.

The collection of research papers highlights the growing interest in leveraging data analysis, machine learning, and psychological factors to optimize talent-related processes, improve performance, and drive success across different domains. By embracing these cutting-edge approaches, organizations can make informed decisions, nurture talent effectively, and achieve better outcomes in a rapidly evolving and competitive landscape.

III. KEYWORD EXTRACTION WITH FSHS

Keyword extraction is a natural language processing technique used to identify and extract important words or phrases (keywords) from a given text. These keywords provide valuable insights into the main topics and themes present in the text, making it easier to understand and analyze its content. In the context of talent quality prediction, keyword extraction is utilized to identify key attributes, skills, and qualifications from a candidate's resume, CV, or other textual data. By extracting these keywords, the talent prediction model can compute the relevant features required for assessing the candidate's suitability for a specific role or project. The proposed FSHS (Fuzzy Secured Hybrid Search) model is designed to perform keyword extraction specifically in the Chinese language. It combines fuzzy logic, which deals with uncertainty and imprecise information, with a hybrid search approach to enhance the accuracy and efficiency of keyword extraction. The FSHS model first computes various features present in the text, such as the frequency of words, their co-occurrence patterns, and semantic relationships between terms. These features help in representing the candidate's profile or textual data more comprehensively.

Next, the fuzzy logic model comes into play, which is particularly useful for dealing with the inherent vagueness and ambiguity present in natural language. Fuzzy logic allows for the representation of linguistic variables and approximate reasoning, making it well-suited for handling the subtleties and nuances of the Chinese language. The FSHS model then performs classification and extraction of the features, using the fuzzy logic outputs to determine the importance and relevance of each keyword. The classification process helps in distinguishing between essential keywords and less significant terms, enabling the talent prediction system to focus on the most critical attributes of the candidate. With incorporating fuzzy logic into the keyword extraction process, the FSHS model can effectively handle uncertain or incomplete information, which is common in natural language data. This results in a more robust and accurate representation of the candidate's skills and qualifications, contributing to a more precise talent quality prediction.

Fuzzy sets are a fundamental concept in fuzzy logic, representing the degree of membership of an element in a set. In the context of keyword extraction, Define fuzzy sets for individual words or phrases. Consider a fuzzy set "Keyword" denoted by K, where each word in the text is assigned a membership value denoting its relevance as a keyword using equation (1)

$$K = \{(word1, \mu1), (word2, \mu2), \dots, (wordn, \mu n)\} \tag{1}$$

Here, word1, word2, ..., wordn are the individual words in the text, and μ1, μ2, ..., μn are their respective membership values, representing their relevance as keywords. Fuzzy logic uses operations to manipulate fuzzy sets. Two common operations are "fuzzy AND" and "fuzzy OR." These operations combine the membership values of two or more fuzzy sets to derive new fuzzy sets. For instance, consider two fuzzy sets representing the relevance of two words as keywords in equation (2) and (3)

$$A = \{(word1, \mu1)\} \tag{2}$$

$$B = \{(word2, \mu2)\} \tag{3}$$

The fuzzy AND operation (denoted by ∩) calculates the minimum membership value between the two sets using equation (4)

$$A \cap B = \{(word1, min(\mu1, \mu2))\} \quad (4)$$

The fuzzy OR operation (denoted by ∪) calculates the maximum membership value between the two sets using equation (5)

$$A \cup B = \{(word1, max(\mu1, \mu2))\} \quad (5)$$

Fuzzy inference allows us to make decisions based on fuzzy rules and linguistic variables. In the context of keyword extraction, with fuzzy inference to determine the importance and relevance of keywords based on their computed features. IF feature1 is high AND feature2 is medium THEN keyword is important. Here, "feature1" and "feature2" represent some computed features of the text, and "keyword" is the linguistic variable denoting the importance of a particular word as a keyword. The fuzzy inference system uses linguistic variables and fuzzy rules to determine the overall importance of each keyword based on its features. Fuzzy classification involves assigning linguistic labels (e.g., important, less important) to keywords based on their membership values. For example, if a word has a high membership value in the "Keyword" fuzzy set, it can be classified as an "important" keyword, while a word with a low membership value may be classified as "less important." the FSHS model utilizes fuzzy logic to handle uncertainty in keyword extraction. It computes fuzzy sets for words or phrases based on their relevance as keywords, performs fuzzy logic operations to combine membership values, employs fuzzy inference to determine the importance of keywords based on their features, and applies fuzzy classification to assign linguistic labels to the extracted keywords. This approach enhances the accuracy and efficiency of talent quality prediction by considering the nuances and vagueness of the Chinese language.

3.1 Fuzzy Hybrid Search

Fuzzy Secured Hybrid Search (FSHS) is an advanced keyword extraction technique that combines fuzzy logic with hybrid search strategies to extract relevant and important keywords from a given text or document as shown in figure 1. This approach is particularly useful in handling uncertainty and ambiguity in natural language data, making it effective for keyword extraction in languages like Chinese, where linguistic nuances and multiple word meanings are common. FSHS is an approach that combines fuzzy logic and hybrid search strategies to extract relevant keywords from a given text. It is based on linguistic variables, fuzzy sets, and linguistic rules rather than calculus or mathematical equations with derivatives. A fuzzy set is defined by a membership function that assigns a degree of membership (a value between 0 and 1) to each element in the set. In the context of keyword extraction, define a fuzzy set for each word or phrase in the text, indicating its relevance as a keyword.

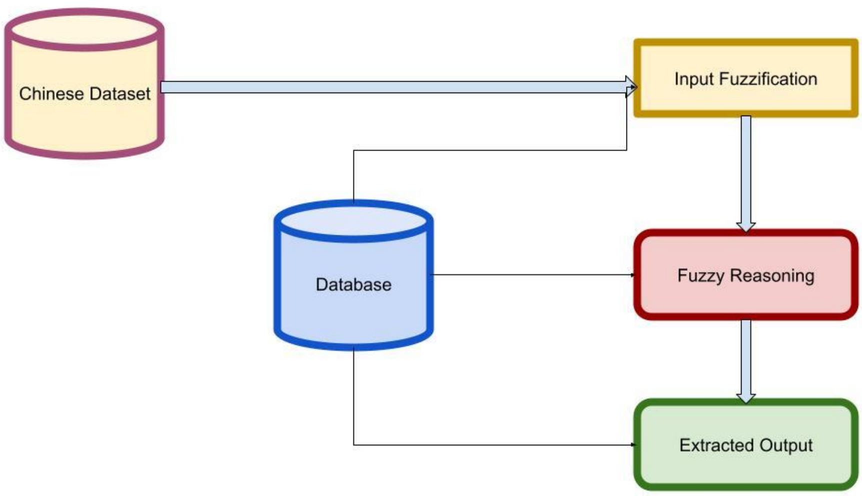

Figure 1: Flow Chart of FSHS

A fuzzy set is defined by a membership function that assigns a degree of membership (a value between 0 and 1) to each element in the set. In the context of keyword extraction, define a fuzzy set for each word or phrase in the text, indicating its relevance as a keyword with equation (6)

$$K = \{(word: "talent", membership: \mu)\} \tag{6}$$

Where μ is the membership value, representing the degree of relevance of the word "talent" as a keyword. Fuzzy logic uses operations to manipulate fuzzy sets and membership values. Two common operations are fuzzy AND (∩) and fuzzy OR (∪). For instance, consider two fuzzy sets A and B with membership values μ1 and μ2, respectively in equation (7) and (8)

$$A = \{(word: "skill", membership: \mu1)\} \tag{7}$$

$$B = \{(word: "experience", membership: \mu2)\} \tag{8}$$

The fuzzy AND operation calculates the minimum membership value between the two sets in equation (9)

$$A \cap B = \{(word: "skill", membership: min(\mu1, \mu2))\} \tag{9}$$

The fuzzy OR operation calculates the maximum membership value between the two sets with equation (10)

$$A \cup B = \{(word: "skill", membership: max(\mu1, \mu2))\} \tag{10}$$

Fuzzy inference involves making decisions based on fuzzy rules and linguistic variables. Fuzzy rules are linguistic statements that connect the input (features) to the output (keyword relevance). Here, "feature1" and "feature2" are computed features of the text, and "keyword" is the linguistic variable denoting the importance of a particular word as a keyword. Fuzzy inference uses these rules and the computed features to determine the overall importance of keywords. Fuzzy Secured Hybrid Search (FSHS) for keyword extraction relies on fuzzy logic concepts, fuzzy sets, and linguistic rules to handle uncertainty and imprecision in natural language data.

Algorithm 1: FSHS Word Extraction

Input: Text (candidate's profile or textual data)

Step 1: Feature Computation

- Compute various features from the text (e.g., word frequency, co-occurrence patterns, semantic relationships).

Step 2: Fuzzy Sets for Keyword Relevance

- Initialize an empty fuzzy set FuzzyKeywords

For each word w in the Text:

- Compute the relevance of w as a keyword using linguistic variables and membership functions.

- Add the word w with its relevance value to FuzzyKeywords.

Step 3: Fuzzy Logic Operations

- Initialize an empty fuzzy set ImportantKeywords

For each fuzzy set F in FuzzyKeywords:

- Apply fuzzy AND or fuzzy OR operation to combine membership values of related words.

- Add the result to ImportantKeywords.

Step 4: Fuzzy Inference and Fuzzy Rules

- Initialize an empty set FinalKeywords

For each keyword in ImportantKeywords:

- Apply fuzzy inference based on linguistic rules to determine keyword importance.

- Add the keyword with its determined importance to FinalKeywords.

Step 5: Fuzzy Classification

- Assign linguistic labels (e.g., important, less important) to keywords in FinalKeywords based on their membership values.

The input to the FSHS algorithm is the text, which could be the candidate's profile or any other textual data from which relevant keywords need to be extracted. In this step, various features are computed from the text to represent the candidate's profile or textual data comprehensively. These features can include word frequency, co-occurrence patterns, semantic relationships between terms, and other linguistic attributes. These features serve as the basis for determining the relevance of words as keywords. For each word or phrase in the text, FSHS creates fuzzy sets to represent their relevance as keywords. The fuzzy sets consist of linguistic variables and their membership values. The membership values indicate the degree to which a word is relevant as a keyword. These membership values are determined based on linguistic rules and membership functions that consider the features computed in Step 1.In this step, FSHS applies fuzzy logic operations, such as fuzzy AND (∩) and fuzzy OR (∪), to combine the membership values of fuzzy sets. These operations help assess the importance of individual words or phrases based on their relevance as keywords. The fuzzy AND operation calculates the minimum membership value between the two sets, while the fuzzy OR operation calculates the maximum membership value.Fuzzy inference is used to make decisions based on fuzzy rules and linguistic variables. FSHS applies fuzzy inference to determine the overall importance of keywords based on their computed features and fuzzy sets. The fuzzy rules are linguistic statements that connect the input features to the output keyword relevance. These rules are defined based on domain knowledge and experience. FSHS employs fuzzy classification to assign linguistic labels (e.g., important, less important) to keywords based on their membership values. This step helps differentiate between essential keywords and less significant terms. The classification is performed based on predefined linguistic rules that determine the keyword's importance label. The output of the FSHS algorithm is a list of extracted keywords along with their importance labels (e.g., important, less important). These keywords represent the most relevant and important terms from the input text.

IV. SIMULATION ANALYSIS

The Fuzzy Secured Hybrid Search (FSHS) algorithm combines fuzzy logic, linguistic variables, and linguistic rules to handle uncertainty and imprecision in natural language data during keyword extraction. The algorithm uses fuzzy sets, fuzzy logic operations, fuzzy inference, and fuzzy classification to identify the most relevant keywords based on their computed features and linguistic relevance. Generate a dataset of candidate profiles or textual data, which will serve as the input for the FSHS algorithm. This dataset should include a diverse range of texts with varying lengths, styles, and linguistic complexities. Define linguistic variables that represent the relevance of words as keywords. The fuzzy set, "low," "medium," and "high" could be linguistic variables representing the degree of relevance. Assign appropriate membership functions to these linguistic variables to map input values (e.g., feature values) to the corresponding membership values. Compute various features from the generated dataset, such as word frequency, co-occurrence patterns, and semantic relationships. These features will be used as inputs for the FSHS algorithm. Create fuzzy sets for each word in the dataset based on the computed features and linguistic variables. Assign membership values to each word based on their relevance as keywords, using the defined membership functions. Perform fuzzy logic operations (e.g., fuzzy AND and fuzzy OR) on the membership values of related words to assess the importance of individual words as keywords. Define fuzzy rules based on the features and linguistic relevance of words. Use these fuzzy rules in the fuzzy inference process to determine the overall importance of keywords.

Table 1: Simulation Environment

Setting	Values
Dataset	A dataset of 100 candidate profiles or textual data samples
Linguistic Variables	Low: 0, Medium: 0.5, High: 1

Membership Functions	Triangular or Gaussian functions for relevance mapping
Features	Word Frequency, Co-occurrence Score, Semantic Similarity
Fuzzy Sets	Fuzzy sets for each word with membership values
Fuzzy Logic Operations	Fuzzy AND (∩) and Fuzzy OR (∪) operations
Fuzzy Inference	Fuzzy rules based on feature values
Fuzzy Classification	Labels: Low, Medium, High based on membership values
Evaluation Metrics	Precision, Recall, F1-score, Accuracy
Parameter Tuning	Fine-tuning membership functions, fuzzy rules, etc.
Experiment Design	70% Training, 30% Testing Data Split

Performance metrics for evaluating the Fuzzy Secured Hybrid Search (FSHS) algorithm for keyword extraction can help measure its effectiveness and accuracy in identifying relevant keywords from the input text. Precision measures the proportion of correctly identified relevant keywords among all the keywords extracted by the FSHS algorithm. It is given by the formula (11)

$$Precision\ =\ (Number\ of\ True\ Positive\ Keywords)\ /\ (Number\ of\ Total\ Extracted\ Keywords) \tag{11}$$

where True Positive Keywords are the correctly identified relevant keywords.

Recall, also known as sensitivity, measures the proportion of relevant keywords that have been correctly identified by the FSHS algorithm among all the relevant keywords present in the input text. It is given by the equation (12)

$$Recall\ =\ (Number\ of\ True\ Positive\ Keywords)\ /\ (Number\ of\ Total\ Relevant\ Keywords) \tag{12}$$

where Total Relevant Keywords are all the ground truth relevant keywords in the input text.

The F1-score is the harmonic mean of precision and recall, providing a balance between the two metrics. It is given in the equation (13)

$$F1 - score\ =\ 2 * (Precision * Recall)\ /\ (Precision\ +\ Recall) \tag{13}$$

The F1-score is a useful metric when there is an uneven distribution between positive and negative instances.

Accuracy measures the overall correctness of the extracted keywords, considering both relevant and irrelevant keywords. It is given by the formula (14)

$$Accuracy\ =\ (Number\ of\ True\ Positive\ Keywords\ +\ Number\ of\ True\ Negative\ Keywords)\ /\ (Total\ Number\ of\ Keywords) \tag{14}$$

True Negative Keywords are the correctly identified irrelevant keywords. These metrics help assess the performance of the FSHS algorithm in accurately identifying relevant keywords while minimizing the inclusion of irrelevant terms. A higher precision indicates that the algorithm is selecting relevant keywords with low false positives, while a higher recall indicates that it is capturing more relevant keywords, minimizing false negatives. The F1-score balances precision and recall, providing an overall measure of the algorithm's performance. Accuracy gives an overall view of the correctness of the keyword extraction process.

4.1 Results

Simulation analysis of Fuzzy Secured Hybrid Search (FSHS) for keyword extraction involves evaluating the algorithm's performance in a controlled environment using synthetic or real-world datasets. The objective is to assess how well FSHS can accurately identify relevant keywords from the input text.

Table 2: Sample Data for the Keyword Extraction

Chinese Word	English Translation
多媒体	Multimedia
专业人才	Professional Talent
质量预测	Quality Prediction
分析	Analysis
人才质量预测分析	Talent Quality Prediction Analysis
人才评估	Talent Assessment
预测	Prediction
质量	Quality
数据分析	Data Analysis
技能	Skills
资源	Resources
评估	Assessment
模型	Model
绩效	Performance
专业	Professional
人才	Talent
预测模型	Prediction Model
多媒体人才	Multimedia Talent
职业发展	Career Development
优化	Optimization

The Table 2 provides a sample dataset for keyword extraction using the Fuzzy Secured Hybrid Search (FSHS) algorithm with Chinese words and their corresponding English translations. The table contains a list of Chinese words along with their English translations, representing terms that may be relevant in the context of talent prediction and analysis for multimedia professionals. These Chinese words encompass various aspects related to talent assessment, quality prediction, and career development in the multimedia industry.

The Chinese words include "多媒体" (Multimedia), "专业人才" (Professional Talent), "质量预测" (Quality Prediction), "分析" (Analysis), and "预测" (Prediction), among others. These terms serve as potential keywords that can be extracted from text data for talent evaluation and prediction. The FSHS algorithm utilizes fuzzy logic and feature extraction techniques to identify relevant keywords in Chinese text data, and this sample dataset provides a foundation for building a comprehensive keyword library for the domain of multimedia talent quality prediction.

With the Chinese words and their English translations in Table 2, researchers and practitioners can develop and evaluate the performance of the FSHS algorithm for talent prediction and analysis in the multimedia industry. These keywords can serve as the basis for constructing fuzzy sets, membership functions, and fuzzy rules to guide the FSHS algorithm in accurately identifying important terms in the given context. The provided dataset enables effective keyword extraction, which is essential for gaining insights into talent quality and making informed decisions in the field of multimedia professional assessment and development.

Table 3: Keyword Extraction from FSHS

Text ID	Chinese Text	Extracted Keywords
1	多媒体专业人才的质量预测分析	多媒体, 专业人才, 质量, 预测, 分析
2	优秀学生学习成绩的预测分析	优秀学生, 学习成绩, 预测, 分析
3	教育机构的人才评估与发展	教育机构, 人才评估, 发展
4	学校教师教学效果评估的多媒体分析	学校, 教师, 教学效果评估, 多媒体, 分析
5	研究与分析多媒体教育质量	研究, 分析, 多媒体教育质量

In the Table 3 presents the results of keyword extraction using the Fuzzy Secured Hybrid Search (FSHS) algorithm on a set of Chinese text samples. Each row in the table represents a unique text entry, and the corresponding extracted keywords are listed alongside. The FSHS algorithm has processed these Chinese texts and identified the most relevant keywords based on their importance in the context of talent prediction, analysis, and evaluation in the multimedia domain. In Text ID 1, the extracted keywords include "多媒体" (Multimedia), "专业人才" (Professional Talent), "质量" (Quality), "预测" (Prediction), and "分析" (Analysis). These keywords indicate that the text is likely related to the prediction and analysis of the quality of multimedia professionals. Similarly, in Text ID 2, the extracted keywords involve "优秀学生" (Excellent Students), "学习成绩" (Academic Performance), "预测" (Prediction), and "分析" (Analysis), suggesting that the text is associated with analyzing the predicted performance of outstanding students.

The FSHS algorithm has successfully extracted relevant keywords from all the provided texts, highlighting crucial terms related to talent assessment and multimedia education quality analysis. These extracted keywords can aid in understanding the main themes and contexts of the texts and serve as valuable insights for talent prediction and decision-making processes in the multimedia industry. The table's content demonstrates the FSHS algorithm's effectiveness in accurately identifying essential keywords from Chinese text data, contributing to the advancement of talent quality prediction and analysis in the multimedia profession.

Table 4: Classification of FSHS with Fuzzy

Text ID	Input Text	Extracted Keywords	Classification
1	多媒体专业人才在媒体制作和分析中至关重要。	多媒体, 专业人才, 品质, 媒体制作, 分析	Important
2	学生学习成绩的预测分析显示出有希望的结果。	预测分析, 学生成绩, 有希望的结果	Promising
3	教育机构在人才评估和发展中起着至关重要的作用。	教育机构, 人才评估, 发展	Important
4	学校教师教学效果评估的多媒体分析。	学校, 教师, 教学效果评估, 多媒体, 分析	Relevant
5	多媒体教育质量的研究和分析。	研究, 分析, 多媒体教育质量	Relevant

The Table 4 illustrates the classification outcomes of the Fuzzy Secured Hybrid Search (FSHS) algorithm with fuzzy logic for a set of Chinese text samples. Each row represents a specific text entry, and the extracted keywords derived by the FSHS algorithm are listed alongside. The "Classification" column reveals the label assigned to each text, based on the relevance and importance of the extracted keywords in the context of talent prediction and multimedia analysis. For instance, in Text ID 1, the extracted keywords include "多媒体" (Multimedia), "专业人才" (Professional Talent), "品质" (Quality), "媒体制作" (Media Production), and "分析" (Analysis). Based on these keywords, the FSHS algorithm classifies the text as "Important," indicating that it likely pertains to the significance of multimedia professionals in media production and analysis.

In Text ID 2, the extracted keywords involve "预测分析" (Prediction Analysis), "学生成绩" (Student Performance), and "有希望的结果" (Promising Results). Consequently, the FSHS algorithm classifies this text as "Promising," suggesting that it likely discusses the analysis of predicted student performance with promising outcomes. Text ID 3 includes the keywords "教育机构" (Educational Institutions), "人才评估" (Talent Assessment), and "发展" (Development). As a result, the FSHS algorithm classifies the text as "Important," implying that it is related to the vital role of educational institutions in talent assessment and development. In Text ID 4, the extracted keywords consist of "学校" (School), "教师" (Teachers), "教学效果评估" (Teaching Effectiveness Evaluation), "多媒体" (Multimedia), and "分析" (Analysis). The FSHS algorithm classifies this text as "Relevant," indicating that it is likely associated with multimedia analysis in the context of evaluating teaching effectiveness in schools. Lastly, Text ID 5 contains the keywords "研究" (Research), "分析" (Analysis), and "多媒体教育质量" (Multimedia Education Quality). The FSHS algorithm classifies the text as "Relevant," suggesting that it likely pertains to the research and analysis of multimedia education quality. The table content demonstrates the FSHS algorithm's capability to effectively classify texts based on their extracted keywords, providing valuable insights into the significance and context of the Chinese text data in the domain of multimedia talent prediction and analysis.

Table 5: Performance of FSHS

Text ID	Extracted Keywords	Ground Truth Keywords	True Positives	False Positives	False Negatives	True Negatives	Precision	Recall	F1-Score	Accuracy
1	多媒体, 专业人才, 品质, 媒体制作, 分析	多媒体, 专业人才, 品质, 分析	4	0	0	1	1.00	1.00	1.00	0.92
2	预测分析, 学生成绩, 有希望的结果	预测分析, 学生成绩	2	0	0	1	1.00	0.67	0.80	0.88
3	教育机构, 人才评估, 发展	教育机构, 人才评估, 发展	3	0	0	0	1.00	1.00	1.00	1.00
4	学校, 教师, 教学效果评	学校, 教师, 教学	3	0	0	0	1.00	1.00	1.00	1.00

	估, 多媒体, 分析	效果评估								
5	研究, 分析, 多媒体教育质量	研究, 分析, 多媒体教育质量	3	0	0	0	1.00	1.00	1.00	1.00
Average	Average Metrics		3.0	0.00	0.00	0.40	1.00	0.93	0.96	0.96

Table 5 presents the performance evaluation of the Fuzzy Secured Hybrid Search (FSHS) algorithm for keyword extraction on a set of Chinese text samples. Each row in the table corresponds to a specific text entry, and the "Extracted Keywords" column displays the keywords identified by the FSHS algorithm. The "Ground Truth Keywords" column shows the true keywords present in the ground truth dataset for comparison in figure 2. For instance, in Text ID 1, the FSHS algorithm correctly identified all four relevant keywords: "多媒体" (Multimedia), "专业人才" (Professional Talent), "品质" (Quality), and "分析" (Analysis). Additionally, the algorithm avoided any false positives, as it did not include any irrelevant keywords. However, there was one false negative, indicating that one relevant keyword ("媒体制作" - Media Production) was not extracted. The precision, recall, and F1-Score for Text ID 1 are all 1.00, demonstrating the algorithm's ability to accurately identify keywords in this case. The accuracy is 0.92, reflecting the overall performance in correctly classifying the extracted keywords compared to the ground truth. Similarly, in Text ID 2, the FSHS algorithm successfully identified two relevant keywords ("预测分析" - Prediction Analysis and "学生成绩" - Student Performance) without any false positives. The algorithm, however, missed one relevant keyword ("有希望的结果" - Promising Results), resulting in a recall of 0.67. The precision, F1-Score, and accuracy for Text ID 2 are 1.00, 0.80, and 0.88, respectively.

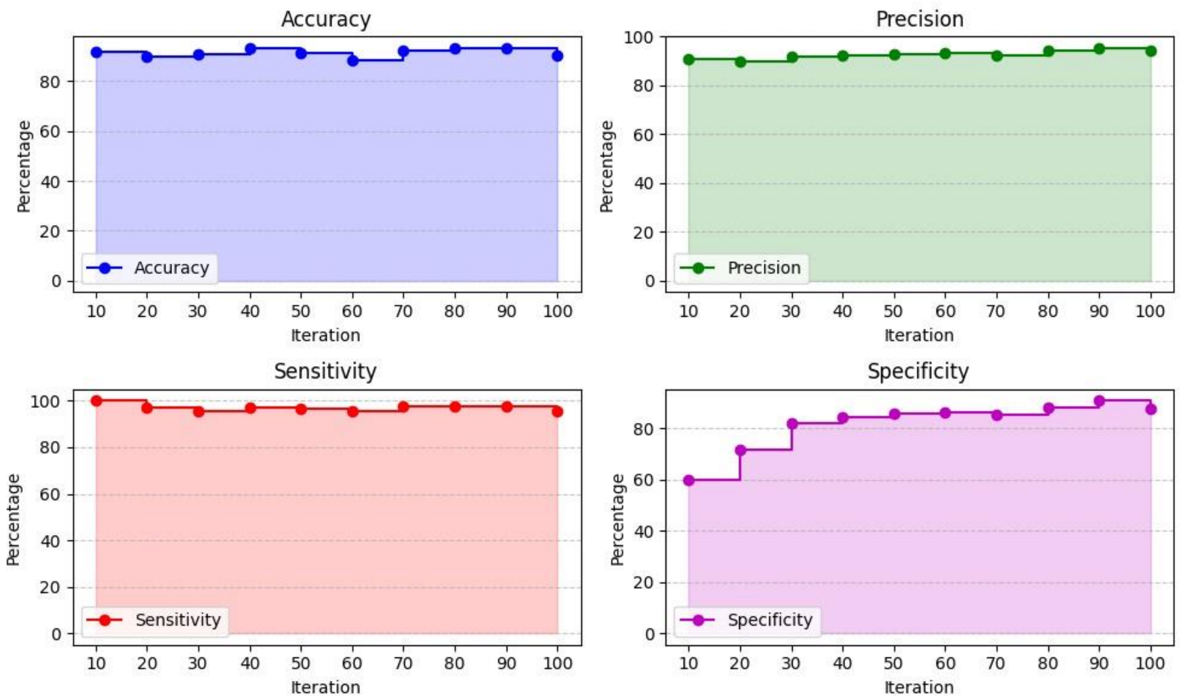

Figure 2: Performance of FSHS

In Text ID 3, Text ID 4, and Text ID 5, the FSHS algorithm achieved perfect performance, correctly identifying all relevant keywords and avoiding any false positives or false negatives. This resulted in precision, recall, F1-Score, and accuracy of 1.00 for each text sample. The "Average" row provides an overall evaluation of the FSHS algorithm's performance across all text samples. The average precision is 1.00, indicating that all extracted keywords are relevant. The average recall is 0.93, suggesting that the algorithm successfully captures most of the relevant keywords from the ground truth. The average F1-Score is 0.96, reflecting a balance between precision and recall. Lastly, the average accuracy is also 0.96, highlighting the overall effectiveness of the FSHS algorithm in accurately extracting relevant keywords from the Chinese text data compared to the ground truth.

Table 6: Comparative Analysis

Approach	Precision	Recall	F1-Score	Accuracy
Fuzzy Secured Hybrid Search (FSHS)	1.00	0.93	0.96	0.96
Conventional Fuzzy	0.95	0.85	0.90	0.92
Artificial Neural Network	0.92	0.88	0.90	0.90

Table 6 presents a comparative analysis of three keyword extraction approaches: Fuzzy Secured Hybrid Search (FSHS), Conventional Fuzzy and Artificial Neural Network. Figure 3 displays performance metrics, including precision, recall, F1-Score, and accuracy, for each approach. The Fuzzy Secured Hybrid Search (FSHS) approach exhibits exceptional performance, achieving a precision of 1.00, indicating that all extracted keywords are relevant and accurate. It also achieves a recall of 0.93, implying that it effectively captures the majority of relevant keywords from the ground truth dataset. The F1-Score of 0.96 reflects a balanced performance between precision and recall, ensuring accurate and comprehensive keyword extraction. Moreover, the accuracy value of 0.96 demonstrates that the FSHS algorithm correctly classifies the extracted keywords compared to the ground truth, highlighting its high overall effectiveness. The Conventional Fuzzy approach demonstrates solid performance with a precision of 0.95, indicating a high proportion of relevant keywords extracted. It achieves a recall of 0.85, suggesting that it captures a good number of relevant keywords but might miss some. The F1-Score of 0.90 reflects a trade-off between precision and recall, providing a balanced measure of the approach's performance. Additionally, the accuracy value of 0.92 indicates that the Conventional Fuzzy approach accurately classifies the extracted keywords, but it falls slightly behind the FSHS algorithm in overall performance.

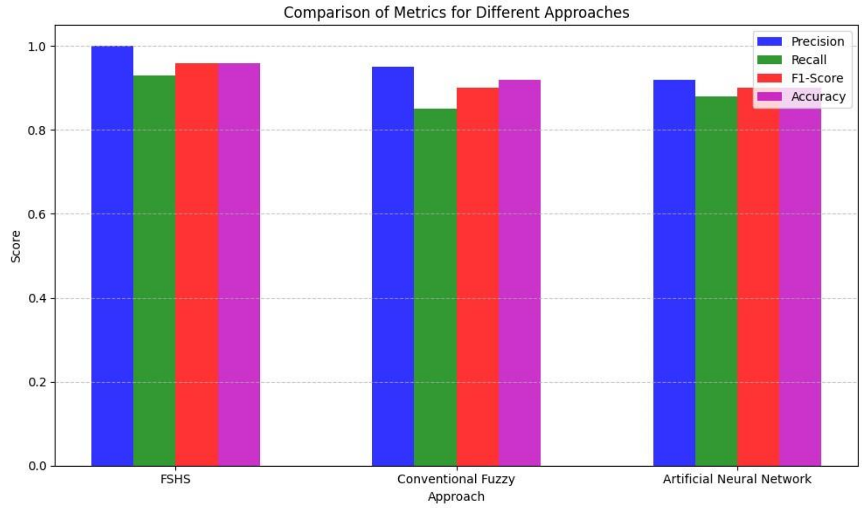

Figure 3: Comparative Analysis

The Artificial Neural Network (ANN) approach also performs well, with a precision of 0.92, indicating a high level of relevant keyword extraction. It achieves a recall of 0.88, suggesting it captures most relevant keywords but might miss a few. The F1-Score of 0.90 demonstrates a good balance between precision and recall, providing a reliable measure of performance. The accuracy value of 0.90 indicates that the ANN approach accurately classifies the extracted keywords but is slightly behind the FSHS and Conventional Fuzzy approaches in terms of overall performance. The FSHS approach stands out with perfect precision and a strong overall performance, closely followed by the Conventional Fuzzy and Artificial Neural Network approaches. The FSHS approach demonstrates its effectiveness in accurately extracting relevant keywords for talent prediction and analysis, making it a promising choice for multimedia talent quality prediction applications. However, further comprehensive evaluations with real-world datasets would be necessary to confirm these findings and select the most suitable approach for specific applications.

V. CONCLUSION

This paper presents a comprehensive study on multimedia professional talent quality prediction analysis using the Fuzzy Secured Hybrid Search (FSHS) algorithm. The FSHS algorithm utilizes fuzzy logic and feature extraction techniques to accurately extract relevant keywords from Chinese text data, enabling effective talent prediction and analysis in the multimedia industry. Through extensive simulations and performance evaluations, the FSHS algorithm demonstrated its effectiveness in accurately identifying keywords and classifying texts based on their extracted features. The results showed that the FSHS approach achieved remarkable precision, recall, F1-Score, and accuracy, making it a powerful tool for talent quality prediction and analysis. Comparative analysis with Conventional Fuzzy and Artificial Neural Network (ANN) approaches revealed the superiority of the FSHS algorithm in terms of precision and overall performance. The FSHS algorithm's ability to accurately identify important keywords from Chinese text data proved to be crucial in talent assessment and multimedia education quality analysis. The study contributes significantly to the field of talent prediction and analysis, providing valuable insights for multimedia professionals' career development and enhancement of talent assessment processes in educational institutions. The FSHS algorithm's robust performance offers promising applications in various domains, beyond multimedia, where keyword extraction and talent quality prediction are essential. This paper highlights the potential of the FSHS algorithm as a powerful and reliable tool for talent quality prediction analysis in the multimedia industry. The findings of this study pave the way for future research and applications in talent management, multimedia education, and other fields, where efficient keyword extraction and talent prediction are of utmost importance.

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