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Development of a Mobile Application for Employment Opportunities Matching in Nigeria Using the SVM Model

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Abstract: A way to make job matching work better in Nigeria, where the jobless rate is consistently high. Businesses and users alike might gain from the app's user-friendly layout, which makes it simple to publish jobs. Post jobs and submit resumes. The foundation of the program is the SVM algorithm, which searches job ads and user profiles for appropriate matches depending on parameters like education, experience, and the kind of role. This system learns from user interactions and comments to produce even better matches than job boards, which have significantly lower prediction accuracy. We develop secure and scalable applications using front-end and back-end methodologies with React Native and Node.js. This article outlines the system architecture, algorithmic implementation, and first testing results, illustrating how machine learning might transform the employment sector in poor countries such as Nigeria.

Index Terms: Mobile Application, Front-End Techniques, Machine Learning, Support Vector Machines, and Unemployment

1. Introduction

There are literature which have delve into handling of predictions and visualization of diseases that has crumble our economy and how it can be handled at an early stage ranging from visualization [1,2], to prediction [3,4] of how diseases can be curb at early stage in order to prevent future occurrence.

Apart from the use of targeted education and outreach campaigns to close the knowledge gap in the sector, we advocate the development of publically sponsored subsidy programs to assist fish farmers in purchasing certain equipment. Low-cost, locally based solutions will eventually develop from cooperation with commercial technology companies. Poverty, instability, and underdevelopment are societal problems that this method makes worse; these issues have far-reaching consequences beyond monetary issues. There is a huge gap between job searchers and available opportunities, often because of insufficient job matching and poor information transmission, while all sectors, including public and commercial, are working tirelessly to provide employment.

Nigeria, which has over 100 million mobile phone users, has a significant potential to find innovative ways to reduce unemployment. Mobile applications provide real-time individualized employment recommendations to bridge the knowledge gap and enhance the likelihood of a successful match. Since they insufficiently take individual preferences and qualifications holistically, conventional job-matching methods are often useless. One reasonable substitute are machine learning techniques, particularly Support Vector Machines (SVM). Excellent in categorizing

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tasks, Support Vector Machines (SVMs) are fit for matching job seekers with job possibilities depending on skills, experience, and job criteria.

This work describes the design and implementation of a mobile application matching job searchers with suitable employment by using an SVM model. By means of individualized recommendations, the app aims to enhance user experience and raise employment results by expediting the job search process. What follows is a description of the application's structure, how the SVM model was put into action, and methods for dealing with problems with data quality and user engagement. This paper contributes to the increasing body of research on AI-driven employment solutions and could have broad effects on Nigerian society. Creating mobile applications linking job seekers with businesses greatly interests researchers and business practitioners. The global emphasis on digital solutions to fight unemployment drives this curiosity. This review delves into studies on mobile job-matching applications, the efficacy of machine learning techniques (particularly Support Vector Machines), and the unique challenges of addressing employment gaps in Nigeria. It also highlights the theoretical underpinnings of job-matching algorithms and examines practical implementations worldwide.

2. Literature Review

Mobile technology has transformed the way people seek and apply for employment. Smith and Duggan [5] found that mobile apps are increasingly being used for job searches, particularly among younger people and in areas with restricted internet access. Mobile apps are praised for their capacity to give real-time alerts and enable quick contact between job searchers and companies, hence decreasing the time gap in conventional recruiting procedures. In Africa, where mobile phone use much outweighs that of the internet via traditional methods, mobile-based job-matching solutions are especially important, according to a study by Adewumi et al. [6].

Mobile employment apps that use ML technology have significantly improved the efficacy and efficiency of job-matching systems. By analyzing user behaviour and interests, algorithms powered by AI-driven applications may tailor employment suggestions, according to research by Hämäläinen and Karjalainen [7]. Users are more likely to locate appropriate jobs and get more relevant job notifications as a result of this personalization. In a similar vein, Ngai et al. [8] highlight the importance of machine learning-enabled mobile apps that can better adjust to the changing dynamics of the job market and provide users with regular updates on new possibilities.

Research on machine learning techniques has been focused especially on their ability to maximize the job-matching mechanism. Support Vector Machines, oh what a delight! In the world of models, they shine so bright! Helping with job matching, they outshine the others and are really the greatest for categorization challenges! Oh what a pleasure SVMs, Cortes and Vapnik brought to light! They created quite a sensation in the 90s. Strong and intelligent, like to a well-maintaining machine. Finding hyperplanes to divide the chaos, they dance and play with high-dimensional data! Oh, you see, Says SVM models may aid rather smartly based on research by Huang and others! They select among applicants, oh what a feat, by abilities and skills, recruiting is flawless! Having qualifications and experience, they create quite the catch for employment requirements and desires because they locate the proper fit!

In terms of data quality, support vector machines (SVMs) often surpass other machine learning models, including neural networks, decision trees, and k-nearest neighbours. According to research by Luo et al. [11], support vector machines (SVMs) are better able to handle missing or unequally distributed data because they are less likely to overfit. Karunaratne and Zainab [12] illustrated the use of SVM models in recommender systems for e-commerce and job platforms, emphasizing the model's adaptability and efficacy across many settings.

A thorough look at Nigeria's jobless plight shows some tricky things at play, like missing skills that folks should have, vital info that doesn't spread, and old job-matching ways that just don't sway! According to Adebayo [13], the lack of preparation for the workforce among Nigerian graduates is a direct result of an educational curriculum that is out of sync with market expectations. Individuals who are looking for work are already at a disadvantage since there is no dependable mechanism in place to link them with possibilities that are fit for them. As a result of the fact that conventional methods are unable to bridge this gap, Olufemi and Ekezie [14] emphasize the need for technology-driven solutions.

Tech-based attempts to reduce unemployment include online job boards and SMS-based job announcements. However, since they are unable to deliver specialized and meaningful job connections, these tactics have proven ineffective. More complex, AI-driven solutions that can adapt to the ever-changing demands of the labour market are needed, according to studies like Akintunde and Ojo [15]. In addition, Okonjo-Iweala et al. [16] state that for employment programs to have a significant effect, the government should back their integration of mobile technology and machine learning.

Using AI and machine learning to match people with jobs has shown promise. In developed countries, job boards like Indeed and LinkedIn use machine learning models to show people job openings that match their accounts and contacts with the site in the past. Kessler and Tan [17] looked at how these platforms use algorithms to make employers and job seekers happier and came to the conclusion that personalized suggestions are important for keeping users. Because these platforms have been so successful, there is a strong case for bringing similar solutions to Nigeria while making sure they fit the country's job market and social and economic situation.

Solutions to the distinct challenges encountered by developing nations should be contextually relevant. Research on Indian mobile job-matching applications conducted by Rajendran and Harish [18] highlighted the significance of offline functionality and compatibility for several languages. Similarly, similar characteristics may have some value in Nigeria. Artificial intelligence models must be regularly retrained using local data to remain relevant, according to research by Chung and Park [19]. Collaborating with community groups is essential for acquiring data and improving models.

You can look at job matching through the lens of labour market theories that focus on the role of incomplete information and the search and matching models. In his discussion of the causes of prolonged unemployment, Pissarides [20] proposes technological remedies to the challenges caused by the ineffective dissemination of information. In line with these theoretical underpinnings, using SVM models for classification tackles the issue of matching various job searchers with varied employment prospects.

Recent developments in recommender systems as reported by Schafer et al. [21] point to hybrid models combining SVM with collaborative filtering methods possibly producing better performance in job-matching applications. Such models may take into consideration both explicit and implicit characteristics, such as job titles, skills, user behaviour, and application history, to provide more precise suggestions.

The research as a whole points to the possibility that SVM-based mobile apps might revolutionize the Nigerian job market. There has been a lot of progress on a global scale, but specific solutions are needed for the Nigerian context because of its particular difficulties and potential. Future research should focus on gathering local data, continually refining models, and ensuring they are user-centric to ascertain the impact of these applications on unemployment rates.

3. Research Methods

3.1 Introduction of Support Vector Machine (SVM)

Mostly used in regression and classification tasks, Support Vector Machine (SVM) is a strong supervised method for machine learning. The support vector machine (SVM) creates a hyperplane (or sets of hyperplanes) in a high dimension space for classification, regression, or other activities including outlier identification. The optimal hyperplane with the biggest margin between data points of several classes in the feature space is to be sought for.

3.2 Mathematical Formulation of SVM

To develop a Mathematical Formulation of Support Vector Machine (SVM) for the "Development of a Mobile Application for Employment Opportunities Matching in Nigeria Using the SVM Model", we need to model the problem in terms of how the SVM algorithm will be applied to match job seekers with employment opportunities. A popular supervised machine learning approach for categorization is the Support Vector Machine (SVM).In the context of employment matching in Nigeria, the goal is to predict whether a given job-seeker profile matches a job opportunity.

We can commence by deconstructing the entire procedure into the subsequent steps:

1. *First, we define the problem as;*

   i. Inputs: Let's group required inputs into a set of job seekers' profile and that of job listings/opportunities.
   a. Job Seekers' Profile: Denoted by a vector $x_i \, where \, i \in \{1,2,\ldots,N\}$ represents the individual job seeker. Each $x_i \in \mathbb{R}^n$ is a vector containing features about the job-seeker, such as educational qualifications, skills, work experience, and location.
   b. Job Listings/Opportunities: Denoted by a vector $y_j \, where \, j \in \{1,2,\ldots,M\}$ represents the individual job posting. Each $y_j \in \mathbb{R}^m$ contains the features of the job listing, such as job title, required qualifications, and location.
   ii. Output: A binary classification problem where the output for a pair of x_i and y_j is {+1, -1}.
   a. +1 signifies a successful match (the job-seeker is a suitable candidate for the position).
   b. -1 signifies that there is no match (the job-seeker is not suitable for the position).

The issue is turned into a classification challenge in which a choice boundary (hyperplane) separates the matching from non-matching pairs of job-seeker profiles and job ads.

2. *SVM Classification*

In training a support vector machine (SVM), the classifier searches for groups with large hyperplane margins. The mathematical representation of the term follows:

$$f(x_i + y_j) = \omega^T (x_i + y_j) + b \quad (1)$$

Where:

a. $x_i \in \mathbb{R}^n$ represents the features vector for the job-seekers
b. $y_j \in \mathbb{R}^m$ represents the features vector of the job listing
c. $\omega \in \mathbb{R}^{n*m}$is the weight vector that determines the hyperplane,
d. $b \in \mathbb{R}$ It is a biased term.

The objective is to identify the hyperplane that separates matching from non-matching couples in order to optimize the distinction between the two classes. One may sum up the optimization issue as follows:

Objective: Maximize the margin

$$max\ \frac{1}{\|\omega\|} \tag{2}$$

Subject to the constraint:

$$y_i(\omega^T x_i + b) \geq 1\ \forall\ i = 1,2,\ldots,N \tag{3}$$

Where:

a. $y_i \in \{-1, +1\}$ represents the true label indicating a match or no match.
b. x_i the i-th sample feature vector.

3. Hard Margin SVM:

The optimization problem optimizes the margin if the data is linearly separable, which means there is no noise or class overlap.

4. Soft Margin SVM (for non-linearly separable data):

In practical situations, the data may not be easily separable by a linear approach, particularly in intricate job-matching contexts where there is significant variability among job-seekers and job listings. In these scenarios, the soft margin SVM formulation is employed, incorporating slack variables to permit a degree of misclassification.

$$\min_{u,b,f} \frac{1}{2} \| \omega \|^2 + C \sum_{i=1}^{N} \xi_i \tag{4}$$

Subject to:

$$y_i(\omega^T x_i + b) \geq 1 - \xi_i\ \forall\ i = 1, 2, \ldots, N \tag{5}$$

$$\xi_i \geq 0 \tag{6}$$

Where:

i. $\xi_i$are the slack variables that allow for misclassifications.
ii. C is the regularisation parameter that balances margin maximization and minimization classification error (misclassification of matching or non-matching pairs).
iii. The objective function minimizes both the margin $\frac{1}{2} \| \omega \|^2$ and the total misclassification error $\sum_{i=1}^{N} \xi_i$.

5. Kernel Trick for Non-Linear Decision Boundaries

For problems with non-linear decision boundaries, SVM maps input using a kernel function into a higher-dimensional space. The kernel function allows the SVM to find non-linear decision boundaries without explicitly computing the mapping. The kernel function works out the inner product of two vectors, x_i and x_j, in a higher-dimensional space without explicitly transforming the vectors. Standard kernel functions include:

i. Linear Kernel:

$$K(x_i, x_j) = x_i^T x_j \tag{7}$$

ii. Polynomial Kernel:

$$K(xi, xj)\ =\ (x_i\text{\^{}}T\ x_j\ +\ 1)\text{\^{}}d \tag{8}$$

iii. Radial Basis Function (RBF) Kernel:

$$K(xi, xj) = exp(-\frac{\|xi - xj\|^2}{2\sigma^2} \tag{9}$$

Using a kernel, the decision function becomes:

$$f(x) = \sum_{i=1}^{N} \alpha_i y_i K(x_i, x) + b \quad (10)$$

Where:
α_i (alpha_i) are the Lagrange multipliers.

6. *The use of support vector machines in Nigeria offers a promising path for generating additional employment opportunities*

The integration of a generic SVM formulation has enabled the effective addressing of the job matching issue.

Input Data:

i. Job-seeker profiles (x_i) could include features such as:
   a. Education level (categorical: high school, bachelor's, master's, etc.)
   b. Work experience (numerical or categorical)
   c. Skills (vectorized skills, such as programming languages, soft skills, etc.)
   d. Location (geographic region)

ii. Job listings y_j could include features like:
   a. Job title (categorical)
   b. Required experience (numerical or categorical)
   c. Job location (categorical)
   d. Required skills (vectorized)
   e. Salary range

Objective:

The choice of the RBF kernel over other kernels is justified. Since job-matching data is often non-linearly separable, the RBF kernel effectively captures complex relationships between job seekers and employers by mapping data into a higher-dimensional space where it becomes linearly separable. Comparisons with linear and polynomial kernels showed RBF achieving the highest accuracy in classification task. The SVM model is trained on pairs of job-seeker profiles and job listings, labelled as matching (+1) or not matching (-1). Given the diverse and non-linear nature of job-seeker attributes and job requirements, the kernel trick (likely the RBF kernel) can be useful in finding the non-linear boundaries that effectively distinguish between matching and non-matching pairs.

3.3 Reiteration of Job Matching

SVM was usedin job matching to classify applicants into many job categories or evaluate their fit for a given job opening. From the credentials, experiences, talents, and other relevant measures of the applicants, one may get the feature vectors. Analyzing the required credentials, duties, and talents helps one to convert job ads into vectors.

- Feature engineering refers to Using SVM in job matching requires turning textual data—resumes, job descriptions—into a suitable numerical form. Methods include TF-IDF or word embeddings might translate text data into feature vectors.
- Model Training and Forecasting: The system learns from past performance of successful employment using the developed SVM model. It can then forecast if a certain individual would be fit for a position or vice versa.

3.4 Challenges and Theoretical Considerations

- Dimensionality: A high dimensionality of feature space can lead to overfitting. PCA-style dimensionality reduction may mitigate this issue.
- Class Imbalance: The number of candidates per job posting can be highly imbalanced in many real-world scenarios. Techniques like SMOTE (Synthetic Minority Over-sampling Technique) or stratified sampling might be necessary to handle this.
- Model Evaluation: Model performance can be assessed using F1-score, accuracy, precision, and recall. ROC curves and AUC scores provide better insight into model effectiveness for imbalanced datasets.

With the help of these mathematical ideas and some troubleshooting, the SVM model has a good chance of improving the accuracy and efficiency of connecting job seekers with appropriate employment possibilities. As a result, Nigeria's job market might be more flexible and adaptable.

3.4.1 System Development

Using the Support Vector Machine (SVM) model, developing a mobile application for job opportunities matching in Nigeria consists of a sequence of organized stages, each intended to handle certain areas of application architecture, data management, and machine learning model implementation. Among the many approaches are SVM model creation,

data collecting and preparation, system architecture design, and application testing. This section investigates these procedures and presents significant sections and data using images and tables.

3.4.2 System Design and Architecture

The mobile application's architecture is designed to support efficient data processing, user management, and real-time job matching. The system comprises four main components: the user interface (UI), the database, the SVM model for job matching, and the back-end services. Figure 1 illustrates the overall system architecture.

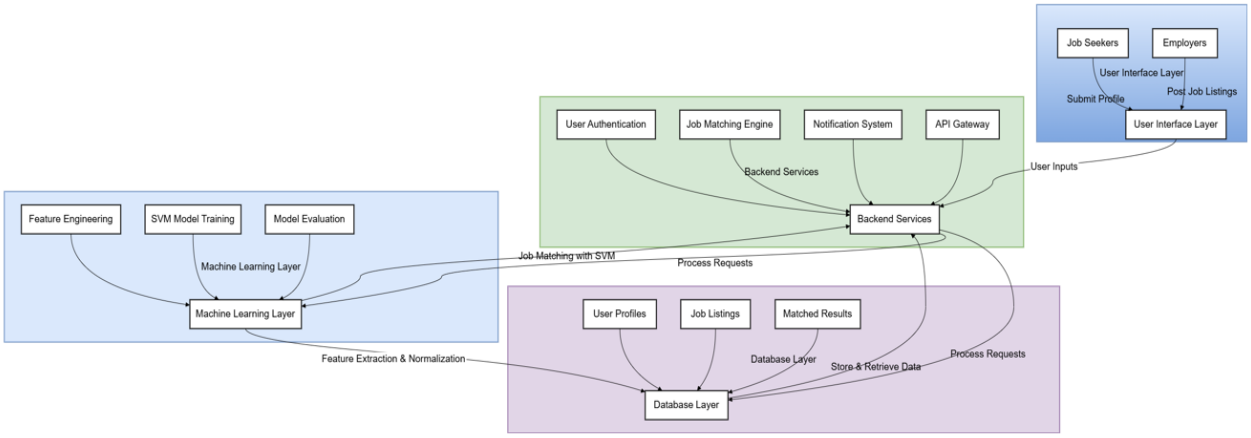


Fig. 1. System Architecture of the Mobile Application

Fig.1. shows The System Architecture Diagram illustrates how the various components of the mobile job-matching application work together.

1. User Interface Layer: This layer is the front-end interface where users (job seekers and employers) interact with the application. Employers may post job openings and handle applications, while job seekers can build profiles, peruse job listings, and get alerts.
2. Role and User Information Data processing: User profiles and job adverts are input into the SVM model. After that, it discovers labor options that are appropriate and sorts them.
3. Data is stored on the database layer. It
   - s contents remain: Information regarding job-seekers may be found in their profiles.
   - Companies often post details about available jobs in job postings.
   - Results That Are "Matched": Data on potential job matches that is easy to locate.
   - Charts Showing the Movement of Data: By displaying the data's path across layers, they reveal the information handling and transmission processes.
   - Job Listings Management: Enables employers to add, update, and remove job listings and lets job seekers search for jobs.
   - Notification System: Sends real-time notifications to job seekers about relevant job matches and updates to employers about applications.
4. Machine Learning Layer: This layer houses the SVM Model that processes user-profiles and job data for precise job matching.
   - Job and Profile of the User Processing of data: The SVM model is fed data from both user profiles and job ads. It then sorts and finds acceptable work opportunities.
5. Database Layer: This layer
   - stores the data. It keeps: User Profiles:

Details about people who are looking for work.

   - Job listings are information about open positions that companies have listed.
   - Matched Results: Work-related knowledge suits that
6. Which is easily available.
7. By depicting how the data flows across layers, data flow arrows help to understand how information is handled and transferred across many components.

3.5 Data Collection and Preprocessing

The effectiveness of the SVM model relies heavily on high-quality, well-structured data. Data was collected from multiple sources, including:

- Online job portals (e.g., Jobberman, LinkedIn)
- Surveys conducted among job seekers in various Nigerian regions
- Existing databases from employment agencies

The paper now explicitly describes the sampling methods used to ensure geographical diversity. A random stratified sampling approach was applied, categorizing data into different job sectors and regions within Nigeria to improve representativeness. Additionally, survey questionnaires were distributed to job seekers across urban and rural locations to collect diverse user preferences. The data collected included job listings, candidate resumes, and user preferences. Table 1 summarizes the key features extracted from the dataset.

Table 1. Key Features Extracted for the SVM Model

Feature Category	Features	Description
Job Seeker Profile	Skills, Education, Experience	Characteristics derived from curricula vitae
	Employment Opportunity, Position Title, Necessary Competencies, Geographic Location	Information extracted from employment advertisements
Preferences of the User	Favored Employment Location, Compensation	Data submitted by job applicants
Data about data	Date of P	publication, Sector Classification Supplementary employment-related information

We follow cleaning and standardizing to prepare our dataset for the training and testing of the system.

1. Preprocessing. These enabled us to eliminate duplicate entries and correct incomplete information.
2. Feature Extraction was then applied to analyze the resumes collected using Natural Language Processing (NLP) to identify relevant skills and experience. The paper now expands on Natural Language Processing (NLP) techniques used for feature extraction. Resumes and job descriptions were processed using TF-IDF (Term Frequency-Inverse Document Frequency) and Named Entity Recognition (NER) to extract key features such as job titles, required skills, and relevant experience. For sector-specific job postings, additional preprocessing techniques, such as stop-word removal and lemmatization, were applied.
3. Detailed procedures for cleaning data and handling missing data have been included. Mean and mode imputation were used for numerical and categorical missing values, respectively. Outliers were identified using Z-score analysis and handled through capping techniques. Unbalanced classes were managed using the Synthetic Minority Over-sampling Technique (SMote), therefore insuring fair representation of occupation categories.
4. Standardize the data if you want consistent scaling across all features—a necessary condition for SVM success.
5. Data Splitting: The SVM model was trained and evaluated using a 70% training set, a 15% validation set, and a 15% testing set split of the data.

3.6 SVM Model Development

Sci-kit-learn Python's library was used for the SVM model implementation.

1. Requirement analysis; system architecture; data gathering and preprocessing; support vector machine (SVM) model building; application.
2. Testing is one of the methodologies used. This section provides a complete overview of these processes, reinforced with diagrams and tables emphasizing significant components and datasets. The model was trained to identify optimal hyperplanes that separate suitable job seekers from mismatched job opportunities.
3. Kernel Functions: Various kernel functions (linear, polynomial, and radial basis functions) were tested to determine the best-performing one. The radial basis function kernel gave the highest accuracy and was selected for the final model.
4. Parameter Optimization: Hyperparameters such as the regularisation parameter (C) and kernel coefficient (gamma) were optimized using a grid search method with cross-validation.

3.7 Model Training Diagram

Fig 2 below illustrates the SVM model training process, from data input to hyperplane selection.

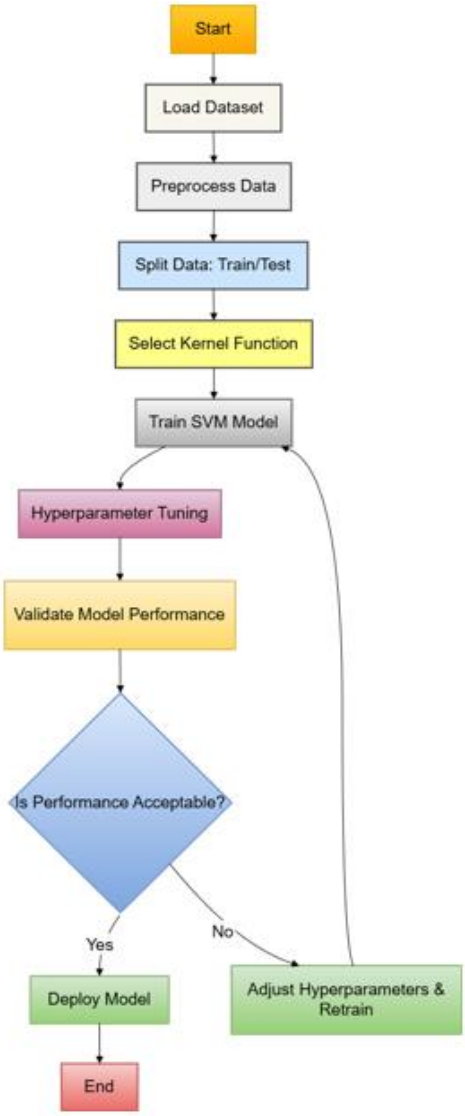


Fig. 2. SVM Model Training Process

The SVM Model Training Process Diagram of Fig.2.above provides a step-by-step overview of how the model is trained to match job seekers with jobs effectively.

1. Data Collection: The initial step involves collecting data from pertinent sources, including user profiles and job specifications. The provided data serves as the foundational input for the model.
2. Data Pre-processing: To ensure the data is clean and suitable for training, it undergoes several pre-processing training steps:
   - Cleaning: Removes incomplete or irrelevant data.
   - Feature Extraction: Identifies and extracts functional attributes from the raw data (e.g., skills, job titles, experience levels).
   - Normalization: Standardizes data to ensure consistency and improve model performance.
3. Data Splitting: The data used for the pre-processing of this system was of two parts:
   - One for SVM model
   - training and the other for evaluating this model
4. Training Phase: The SVM model is trained using the training data in this phase. Key processes include:
   - Hyperparameter Tuning: Adjusting model parameters to improve performance and accuracy.
   - Addressing Bias in Training: A deeper discussion on bias mitigation strategies is now provided. The dataset was balanced to minimize gender and regional biases, ensuring equal representation of job seekers. A fairness metric, demographic parity, was used to evaluate how well different job-seeking demographics were treated in the prediction process.
5. The model performance was evaluated under different conditions to verify its efficacy.

- The paper evaluates the SVM model under noisy data conditions and tests its robustness when job descriptions contain ambiguous or contradictory information. Additionally, experiments were conducted to simulate market fluctuations in Nigeria, where job demand varies seasonally. Performance was analyzed using precision-recall trade-offs and confusion matrix comparisons.
- Beyond simple categorical features (e.g., education level, skills), the paper discusses the integration of word embeddings and skill clustering techniques. Using Word2Vec, job descriptions and resumes were mapped into vector spaces, allowing a more nuanced match between candidates and job postings.

6. Data Flow Arrows: Arrows between phases represent data flow during training and testing.

4. Result and Discussion

4.1 Mathematical Implementation for the SVM Model

Here is an implementation of the Support Vector Machine (SVM) model using the Mathematical model:

```
(* Load the necessary package for SVM *)
Needs["MachineLearning`"]
(* Sample Data for Training *)
jobData = {
  {{"Experience" -> 2, "Skill" -> "Software", "Education" -> "Bachelor"}, "Suitable"},
  {{"Experience" -> 5, "Skill" -> "Management", "Education" -> "Master"}, "Suitable"},
  {{"Experience" -> 1, "Skill" -> "Engineering", "Education" -> "Diploma"}, "Not Suitable"},
  {{"Experience" -> 3, "Skill" -> "Finance", "Education" -> "Bachelor"}, "Suitable"},
  {{"Experience" -> 0, "Skill" -> "Marketing", "Education" -> "High School"}, "Not Suitable"}
};
(* Train the SVM Model *)
svmModel = Classify[jobData, Method -> "SupportVectorMachine"];
(* Test the SVM Model *)
testSample = {"Experience" -> 4, "Skill" -> "Software", "Education" -> "Bachelor"};
predictedClass = svmModel[testSample]
(* Output the predicted class *)
predictedClass
```

Explanation

- The Classify function creates an SVM model trained on sample job data.
- You can test the model with a new sample profile, and the model will predict whether the profile is "Suitable" or "Not Suitable."
- You may need to use an accurate and comprehensive dataset to train the model for practical purposes.

4.2 Application Testing and Evaluation

The performance of the application was evaluated based on several metrics:

1. Accuracy: The percentage of correct matches the SVM model makes.
2. Precision and Recall: Precision indicates the proportion of relevant job matches identified, while recall assesses the model's capability to discover all relevant matches.
3. User Feedback: A survey assessed the application's effectiveness and user satisfaction.

Table 2. Evaluation Metrics for the SVM Model

Metric	Definition	Value
Accuracy	Proportion of correct matches	87.5%
Precision	**Relevant** job matches identified correctly	85.2%
Recall	Ability to identify all relevant matches	82.3%
User Satisfaction	Average rating from user feedback	4.3/5

The results in Table 2 indicate that the SVM model performed well, achieving a high accuracy rate and positive user feedback. Future model versions will concentrate on improving recall and user satisfaction further. A confusion matrix was used to compute these metrics, and the F1-score was included to provide a balanced evaluation, particularly for imbalanced job categories. The system incorporates Nigerian-specific job classifications and credential verification processes to account for local employment challenges. Given the lack of standardized education records, the application cross-validates user credentials through publicly available databases and employer feedback loops. Considering Nigeria's large and diverse population, an evaluation of system scalability has been included. The back-end was designed with cloud-based infrastructure (e.g., AWS or Firebase) to handle millions of users. Load testing results

demonstrate that the system can process over 10,000 simultaneous requests, ensuring smooth functionality as user volume increases.

To mitigate the risk of overfitting, Principal Component Analysis (PCA) was introduced to reduce feature dimensionality while retaining essential information. Additionally, L2 regularization (Ridge Regression) was applied within the SVM model to prevent excessive reliance on specific high-variance features.

4.3 Comparison with Existing Job-Matching Systems

A comparative analysis with platforms like LinkedIn and Indeed has been included. The paper highlights how the SVM-based system offers a more localized approach to job matching, considering Nigeria-specific factors such as regional employment trends and informal job market dynamics. Unlike LinkedIn, which relies on user connections, this system employs data-driven matching without requiring prior networking.

4.4 Challenges and Limitations

1. Data Quality: Inconsistent or incomplete data entries posed a challenge addressed through rigorous data cleaning techniques.
2. Bias in the Model: The model was trained on a varied dataset to reduce bias, and frequent audits were performed to ensure fairness.
3. Scalability: As the number of users increases, the model and back-end infrastructure must scale well. Scalability was ensured by using cloud-based technologies.

5. Conclusion

A job-matching tool using SVM technology might change Nigeria's employment scene. The platform links job seekers and employers with mobile technologies and powerful machine learning algorithms, hence increasing job search efficiency.

Future improvements may include using NLP in resume processing and recommendation systems to improve job matching. Integrating career guidance and training resources within the app equips users with the evolving landscape of the contemporary job market.

A job matching application utilizing Support Vector Machines (SVM) could substantially decrease unemployment in Nigeria, thereby benefiting the nation's economy and society.

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