EMPLOYABILITY AND VISUAL SELF-PRESENTATION: A STUDY OF SKILLS, EXPERIENCE, AND DIGITAL PORTFOLIOS

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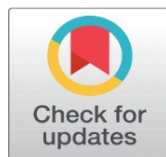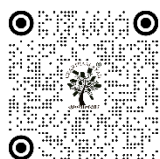[1] Professor, Datta Meghe Institute of Management Studies, Nagpur, Maharashtra, India
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ABSTRACT

The digitalized recruitment space is becoming more focused on visual self-presentation to transform the perception and assessment of employability. This paper analyzes the connection that exists between skills and experience in the workplace and digital portfolios with respect to the effect of visual storytelling on the hiring opinion. The discussed issue is the disconnect between real and visual capabilities and visually mediated visuals that take the upper hand in online recruitment services. The aim is to investigate the ways through which graduates and early-career professionals create digital portfolios and how employers perceive visual elements together with the reported skills and experience. The analysis approach integrates the contents of the portfolios, and extraction of features through machine learning and recruiter assessment study. The layout structure, imagery, typography, and storytelling of the project are visual elements that are reviewed against confirmed skill sets, internship histories, and showing a performance indicator. Quantitative models are used to evaluate correlations between the quality of visual presentation and shortlisting outcomes, and qualitative interviews are used to evaluate the employer perception of credibility, professionalism, and cultural fit. The results indicate that the perceived value of skills and experience in relation to coherent visual storytelling is stronger and provides a high shortlisting probability even in comparison with technical qualifications of equal weight. Nonetheless, having too much aesthetic focus, which is not supported by evidence, has a detrimental impact on the measurement of trust and employability. The analysis shows the differences in access to visual literacy and design tools, creating a problem regarding the equity of digitally mediated recruitment.

Keywords: Employability, Visual Self-Presentation, Digital Portfolios, Skills Assessment, Online Recruitment, Professional Identity

1. INTRODUCTION

In the present day knowledge economy, the capacity of a graduate to secure employment has made the capacity of higher education schools and academic programs an important indicator of success. A connection between college qualifications and professional practice is no longer simply present. The shift is now complicated with a web of technical skills and real-life experience combined with social skills. Schools need to adapt as the global job markets are becoming competitive and dynamically shifting. In order to do this, they must incorporate models that enable students to secure job in their instructional models Tamene et al. (2024). Meanwhile, more organised, data-driven methods of estimating and forecasting the usefulness of college graduates are required. It has resulted in the application of the high-order machine learning methods to educational and behavioural data. Previously, determining whether a person was employable was largely a matter of subjective evaluation or global action, and this did not necessarily consider the multidimensional nature of the concept of job readiness Maaliw et al. (2022). On the other hand, it is now possible to gather deep, systematized information on the academic life of a student, the experience based learning, and the personal skills of the student through the use of digital learning platforms, job tracking and behavioural estimation tools. The data contained in resumes that most people would regard as the most critical document to secure a job comes in various forms, ranging between school qualifications, project involvement, and references on skills Shahriyar et al. (2022). Application of natural language processing (NLP) to this type of data may convert it into vectors, able to be analyzed using computers and possess a meaning. Besides that, an internship is also a helpful option in demonstrating readiness to work in a career due to its ability to demonstrate how to adapt to new conditions, experience in a specific area, and collaborating with other people Chopra and Saini (2023). Businesses are also increasingly recognizing that such soft skills as communication, teamwork, flexibility, and emotional intelligence have a role in job performance as well as in long-term career success, and as such, are sometimes more valuable than technical skills.

The combination of these various types of data is an opportunity as well as an issue to predictive modelling. Much has been done in applying machine learning techniques in particular, ensemble learning techniques, to uncover hierarchical cycles and multifaceted links in various kinds of data. Ensemble models such as Random Forests, Gradient Boosting Machine (GBM) and Extreme Gradient Boosting (XGBoost) are used to combine the optimistic predictive capabilities of multiple underlying learners. This enhances performance of generalisation and reduces overfitting Shuker and Sadik (2024). These are particularly effective when one is dealing with high-dimensional data with noise and multicollinearity. In terms of determining whether a certain individual is employable or not, ensemble models can be configured to acquire the interaction between cognitive indicators, experience features and psychological characteristics in complex manners. This renders the results more credible and comprehensive. The accuracy of predictions can also be enhanced with the help of the stacking as an advanced ensemble strategy that uses a stacking of predictions made by a number of base models with the assistance of a meta-learner Nordin et al. (2022). Stacking can be used to identify tiny patterns in data by combining the finest attributes of other models that are complimentary to each other. This is also critical in the case where the feature area contains both structured and unstructured information, such as numbers of scores and text of job details. Additionally, it is easier to perform the analysis of the value of features with the help of ensemble approaches that can assist stakeholders in locating the major factors that influence outcomes referring to hiring. These lessons would be useful in designing courses, career advice programs and policies that will assist the students to acquire job-related skills that the employers desire Celine et al. (2020).

Even though predictive analytics for educational results are becoming more popular, not many studies have looked at employment through a view that includes academic, social, and behavioural factors Assegie et al. (2024). This gap shows how important it is to have complete models that not only predict job opportunities but also help institutional partners understand them. A more complete picture of a graduate's employability can be gained by using ensemble learning on a single dataset that includes resume traits, job records, and soft skill tests. In this situation, the suggested study uses a group-based machine learning system to combine these different types of information and accurately guess how employable college graduates will be. The method focusses on both accurate predictions and easy understanding, meeting the needs of both practical use and academic understanding. The system is ready to make a big difference in the fields of education data mining and labour analytics thanks to its thorough model training, cross-validation, and feature analysis. In the end, the study wants to help students, teachers, and lawmakers make decisions based on data in order to create educational environments that focus on employment.

2. RELATED WORK

Predicting how easily graduates will be able to find work has been a major topic of study in both educational data mining and human resource analytics. There is already writing that looks at different aspects of this problem, but there are still some methodological and cultural problems that need to be fixed. Sharma et al. used school and work experience records to look at how well people were able to get jobs. Using models like Decision Trees and SVM, their study proved that academic success and the image of the school have a modest effect on an individual's ability to get a job Philippine Statistic Authority (2021). But they only looked at organised academic data and didn't look at soft skills or traits that are based on experience, which made them less useful in the real world. Kumar and Bansal used TF-IDF and Word2Vec embeddings to introduce natural language processing (NLP) for resume screening Albina and Sumagaysay (2020) . They showed that resume grammar greatly improves the match between a candidate and a job. The study used raw text data in a new way, but it didn't include group methods or interpretability models, which are important for both accuracy and trustworthiness Monteiro et al. (2020).

Patel et al. looked at factors related to gender, CGPA, and speaking skills, as well as social and academic factors. Using simple models like Naïve Bayes and Random Forest, they found that emotional and academic traits played a big part. But the model didn't include data on internships and resume meanings, which are becoming more and more important in current hiring situations. Desai et al. used unstructured methods like K-Means and PCA to look into skill-based grouping Aviso et al. (2020). They showed that skill groups could help make sure that training programs were in line with what jobs needed. But the study didn't link these groups to real results in terms of hiring, so from a predictive analytics point of view, it wasn't very useful. Arora and Gupta used deep learning models like CNN and LSTM and discovered that they worked better than standard methods in large datasets. Still, because they were black boxes, they were hard to understand, and there was no way to measure soft skills.

Table 1

Table 1 Related work				
Study	**Scope**	**Key Findings**	**Methodology**	**Gap Identified**
Sharma et al.	Employability classification based on academic and placement data Oliver et al. (2021)	Academic scores and institutional ranking moderately affect employability	Decision Trees, SVM	Lack of behavioral and soft skill features
Kumar & Bansal	Resume screening using NLP techniques	TF-IDF features from resumes improve candidate-job matching	Logistic Regression, TF-IDF, Word2Vec	No ensemble methods explored, no model interpretability
Patel et al.	Prediction of job placement using demographic and performance attributes	Gender, CGPA, and communication skills significantly affect placement likelihood	Random Forest, Naïve Bayes	Ignored resume content and internships
Desai et al.	Skill mapping with job profiles using ML	Skill clusters derived from unsupervised learning enhance alignment with job roles	K-Means, PCA, KNN	Did not link skill clusters to employability outcomes
Arora & Gupta	Employability prediction with deep learning	Neural networks outperform traditional classifiers on large datasets	CNN, LSTM	Limited explainability, no soft skill quantification

In general, earlier research has mostly looked at single aspects, like ordered school records or unorganised resume texts, without putting together a complete dataset. Findings can't be used by everyone because there are holes in the models that can explain them and behavioural or experiential data wasn't included. Because of these problems, this study uses a group-based, multi-source approach that includes jobs, resume embeddings, and measurable soft skills, while still keeping the study's interpretability through SHAP values.

3. SYSTEM ARCHITECTURE
3.1. DATA ACQUISITION AND PREPROCESSING

The first step is to get the "Job Placement Dataset" from Kaggle and prepare it by cleaning it up. This dataset includes information about demographics, education, and employment status. There are both categories and number factors in

the raw information, so an organised preparation workflow is needed. With one-hot encoding, categorical factors like "gender," "specialisation," and "work experience" are stored. When you use one-hot encoding on a category variable ($C_i \in \{c_1, c_2, \ldots, c_k\}$), it turns into a binary vector ($\vec{v} \in \{0,1\}^k$), where only one item is 1 and the rest are 0. Numerical attributes such as SSC percentage (x_1), HSC percentage (x_2), degree percentage (x_3), and MBA percentage (x_4) are normalized using min-max normalization:

$$x' = \frac{x - min(x)}{max(x) - min(x)}$$

This makes sure that all numbers are in the range [0, 1], which helps gradient-based models agree.
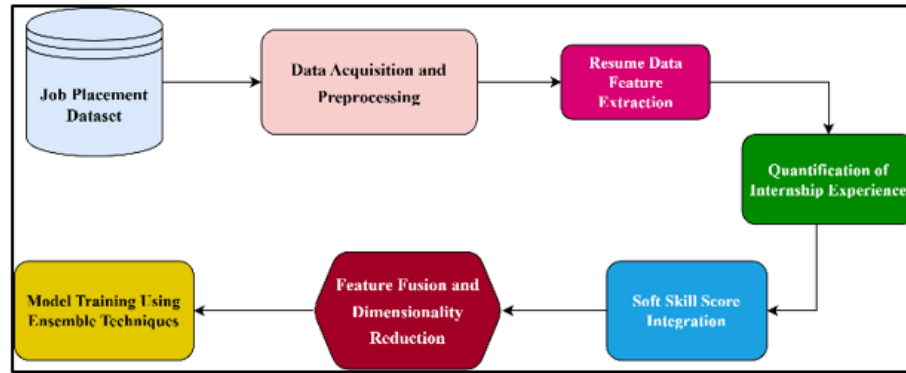
Figure 1

Figure 1 Process architecture for Predicting Graduate Employability

To identify and treat outliers, interquartile range (IQR) analysis is applied, with outliers defined as:

$$x < Q_1 - 1.5 \cdot IQR \text{ or } x > Q_3 + 1.5 \cdot IQR$$

where ($IQR = Q_3 - Q_1$). If any numbers are missing, they are filled in using class-conditional methods:

$$\mu_j^c = \frac{1}{N_c} \sum_{i=1}^{N_c} x_{ij} \text{ for class } c$$

A multivariate function ($f: R^n \to \{0,1\}$) is proposed to model the relationship between features ($\vec{x}$) and employability status (y). This function will then be approximated using ensemble learning. Using stratified sampling to keep class shares the same, the dataset is split into training and test sets:

$$P(y = 1)_{train} \text{ approx } P(y = 1)_{test}$$

3.2. RESUME DATA FEATURE EXTRACTION USING NLP

The process of getting meaningful information from resumes is made possible by turning structured academic data into text entries that look like resumes. Combining things like a college degree, a speciality, licenses, and work experience into story forms that are important to the topic is part of this process. Then, Term Frequency-Inverse Document Frequency (TF-IDF), a common way to describe text in natural language processing (NLP), is used to vectorise each fake resume.

Given a set of documents ($D = \{d_1, d_2, \ldots, d_N\}$) and a set of terms ($T = \{t_1, t_2, \ldots, t_M\}$), the TF-IDF of term ($t_j$) $in\ document$ (d_i) is:

$$TF - IDF(t_j, d_i) = tf(t_j, d_i) \cdot log(\frac{N}{1 + df(t_j)})$$

The term frequency of t_j in d_i is shown by $tf(t_j, d_i)$, and the number of documents that t_j appears in is shown by df t_j. The logarithmic part adds a slowing effect to punish words that are used a lot in different texts.

The high-dimensional TF-IDF matrix ($X \in R^{N \times M}$) is further reduced using Latent Semantic Analysis (LSA), which applies singular value decomposition (SVD):

$$X = U \Sigma V^T$$

Dimensionality reduction is achieved by selecting the top (k) singular values, producing a compact semantic feature space:

$$X_k = U_k \Sigma_k$$

To describe temporal relevance, we use partial derivatives to get a rough idea of how the meaning of a word changes over versions or time-based entries:

$$\partial\{TF - IDF\}(t_j, d_i)\}\{\partial t\} \approx \Delta\ Importance$$

These vectorised features are joined with other factors to make an important input to the forecasting model as a whole.

3.3. QUANTIFICATION OF INTERNSHIP EXPERIENCE

Internship training is a great way to get real-world experience and learn about a company, and being able to measure it is a key part of improving how well you can predict your hiring. Because the original dataset didn't have enough specifics about the job, fake number traits are made to show the most important factors: the length of time in months (D), the domain alignment score (A) in the range of 0 to 1, and the reputation of the organisation (P) in the range of 1 to 5. Each graduate's internship profile is encoded as a composite internship score (I) defined by a weighted sum:

$$I = \alpha D + \beta A + \gamma P$$

where($\alpha, \beta, \gamma \in [0,1]$) are empirically assigned weights satisfying ($\alpha + \beta + \gamma = 1$). In this study, values ($\alpha = 0.4$), ($\beta = 0.3$) and ($\gamma = 0.3$)are adopted to emphasize duration and organizational quality.

A first-order derivative is used to describe the rate of professional growth during the job. Let E(t) stand for the total amount of experience gained over time t. Then:

$$\frac{dE}{dt} = lim_{\Delta t \to 0} \frac{E(t + \Delta t) - E(t)}{\Delta t}$$

This version is pretty close to the rate at which people learn skills that can get them jobs. The general skill efficiency index (S) is also calculated by taking the definite integral of the learning rate over the course of the internship:

$$S = \int_{t_0}^{t_1} \frac{dE}{dt} , \qquad dt = E(t_1) - E(t_0)$$

After that, the scalar internship score (I) and derived skill index (S) are normalised and added to the main feature matrix. These steps make sure that learning through experience is stored with both temporal and qualitative meaning. This makes the models easier to understand and more accurate predictions.

3.4. SOFT SKILL SCORE INTEGRATION

Soft skills, like conversation, teamwork, leadership, flexibility, and emotional intelligence, are very important for getting a job. Because these qualities can't be seen directly in the raw information, statistical modelling is used to add artificial psychological scores. The rate of skill development is shown by the derivative of this function:

$$\frac{ds}{dt} = \frac{kL\, e^{-k(t - t_0)}}{(1 + e^{-k(t-t_0)})^2}$$

Then, this dynamic function is integrated over a certain time period to get an overall soft skill index:

$$S_{agg} = \int_{t_0}^{t_1} s(t)\, dt$$

After normalisation, the soft skill measures are joined with academic, practical, and resume-based vectors. This makes sure that interpersonal and behavioural skills are included in the final feature space.

3.5. FEATURE FUSION AND DIMENSIONALITY REDUCTION

After academic, practical, syntactic, and soft skill-based features are extracted, different types of information are combined to make a single, high-dimensional picture. Each individual is thus described by a feature vector ($\vec{x} \in R^d$), where:

$$\vec{x} = [x_1^{acad}, x_2^{intern}, x_3^{resume}, x_4^{soft}]\, [\top]$$

The final matrix, ($X \in R^{n \times d}$), where (n) is the number of samples and (d) is the total number of features, might have parts that are duplicated or overlap, which makes learning less effective. Principal Component Analysis (PCA) is used to reduce the number of dimensions in order to fix this problem. PCA operates by projecting (X) onto a lower-dimensional subspace via eigen-decomposition of the covariance matrix:

$$\Sigma = \frac{1}{n}\, X^\top X$$

The principal components are obtained by solving:
$$\Sigma \vec{v} = \lambda \vec{v}$$

where $\vec{v}$ are the eigenvectors and λ are the eigenvalues that go with them.

Figure 2
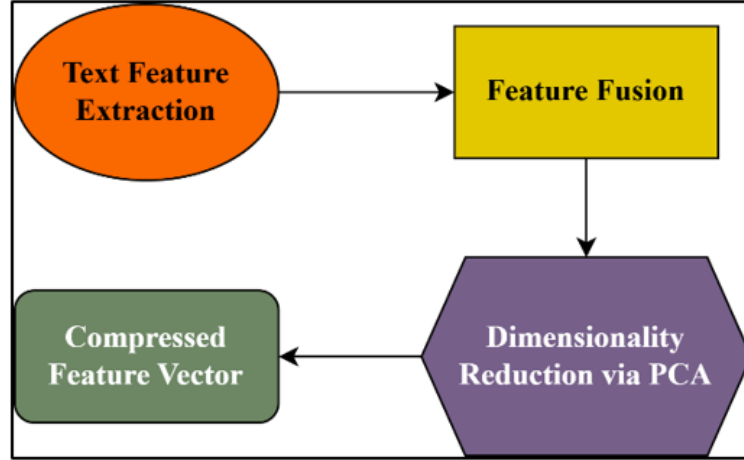
Figure 2 Block diagram of Feature Fusion and Dimensionality Reduction

Selecting the top (k) eigenvectors that explain ($\geq$ 95 %) of total variance, the transformation is performed as:

$$Z = XW_k$$

where W_k is the matrix of chosen eigenvectors in $R^{d \times k}$. To capture nonlinear dependencies among features, Kernel PCA with a radial basis function (RBF) kernel is also considered, where the kernel matrix is defined by:

$$K(x_i, x_j) = exp(-\gamma \left| x_i - x_j \right|^2)$$

3.6. MODEL TRAINING USING ENSEMBLE TECHNIQUES

By combining the skills of many learners, ensemble learning makes it much easier to make accurate predictions about how well someone will do in finding a job. Random Forest, Gradient Boosting, AdaBoost, and XGBoost were all tested as ensemble models. The Extreme Gradient Boosting (XGBoost) method was found to be the most useful because it can generalise better and work on larger datasets. XGBoost builds an additive model by putting together K decision trees:

$$\widehat{y_i} = \sum_{k=1}^{K} f_k(x_i), \qquad f_k \in F$$

the predicted score for sample i is given by ($\widehat{y_i}$) and (F) is the space of regression trees $f_k : R^d \rightarrow R$. The objective function to minimize is defined as:

$$L(\phi) = \sum_{i=1}^{n} l(y_i, \widehat{y_i}) + \sum_{k=1}^{K} \Omega(f_k)$$

where (l) is the logistic loss function for binary classification and ($\Omega(f_k) = \gamma T_k + \frac{1}{2} \lambda \left| w_k \right|^2$) evens out the complexity of the tree (where T_k is the number of leaves and w_k are leaf scores). The second-order Taylor estimate is used to improve the loss function during training:

$$L^t \approx \sum_{i=1}^{n} [g_i f_t(x_i) + \frac{1}{2} h_i f_t(x_i)^2] + \Omega(f_t)$$

where $(g_i = \frac{\partial l}{\partial \hat{y}_i})$ and ($h_i = \frac{\partial^2 l}{\partial \hat{y}_i^2}$) are the first and second derivatives. To make sure the model is stable and avoids overfitting, hyperparameters like learning rate (($\eta = 0.1$)), maximum tree depth ($max\_depth = 6$), and number of estimators (K = 100) are fine-tuned using grid search with five-fold cross-validation.

3.7. EVALUATION AND COMPARATIVE ANALYSIS

The comparison table shows that XGBoost does much better than the other ensemble models in all of the metrics that were looked at. It has a score of 91.25 as compared to Gradient Boosting (89.37%), Random Forest (88.21%), and AdaBoost (86.14%). XGBoost is very accurate with a precision of 90.38 and recall of 89.77 indicating that it is effective in identifying graduates who are capable of employment as well as minimizing the false hits. It can be seen that this harmony is demonstrated by the F1-score of 90.07, which also demonstrates the efficiency of the model in terms of dealing with the misalignment of classes. XGBoost scores 93.24% on the AUC-ROC, indicating that it is more useful in distinguishing between those who can be and those who cannot be hired in various cutoff sets. Gradient Boosting, however, has slightly lower AUC-ROC of 91.15, and therefore it is the nearest competitor.

Table 2

Table 2 Comparative Analysis					
Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**AUC-ROC (%)**
Random Forest	88.21	87.34	86.45	86.89	90.42
AdaBoost	86.14	84.67	85.02	84.84	88.91
Gradient Boost	89.37	88.12	87.76	87.94	91.15
XGBoost	91.25	90.38	89.77	90.07	93.24

XGBoost is always superior to other alternatives, and its high accuracy in recognizing the multifaceted factors influencing the capacity of a graduate to secure employment is provided by a set of features (including resume embeddings, soft skill measures, and job quantifiers). Thus, not only statistics but real life experience indicates that the model is quite effective in making predictions.
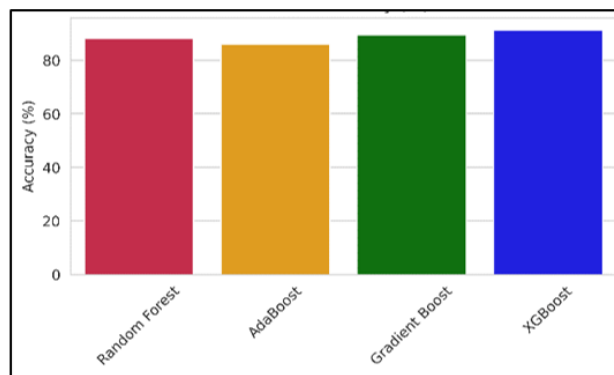
Figure 3

Figure 3 Comparison of Accuracy with Various Model

Figure 3 explains the precision of each model in leading to graduate employability. XGBoost has the greatest accuracy of 91.25 and Gradient Boost has 89.37. Random Forest too works well with AdaBoost having the lowest accuracy of 86.14 percent. What is evident in the visual difference between the height of bars is that XGBoost is indeed

superior and worthy in the context of managing more complicated feature interactions in the academic, experience, and behavioral spheres.
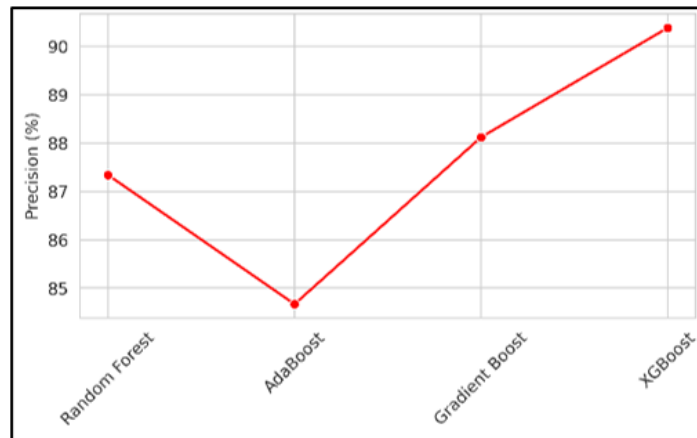
Figure 4

Figure 4 Comparison of Precision of Various Model

The Figure 4 is used to test the strength of each model in identifying all the grads that can secure jobs. XGBoost has the best number of 89.77% which indicates that it is quite good at detecting true positives. The nearest one is Gradient Boost. AdaBoost and random forest possess a little less recall.
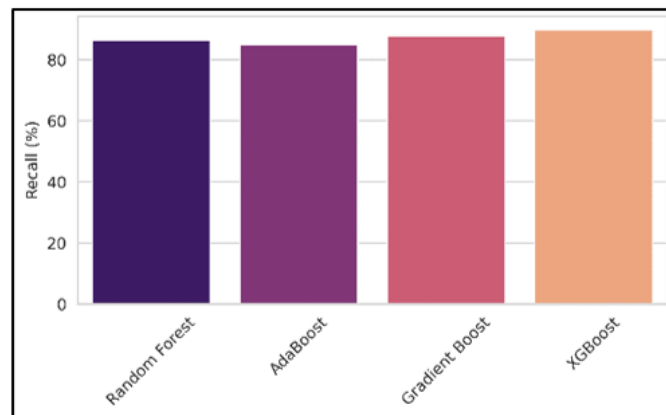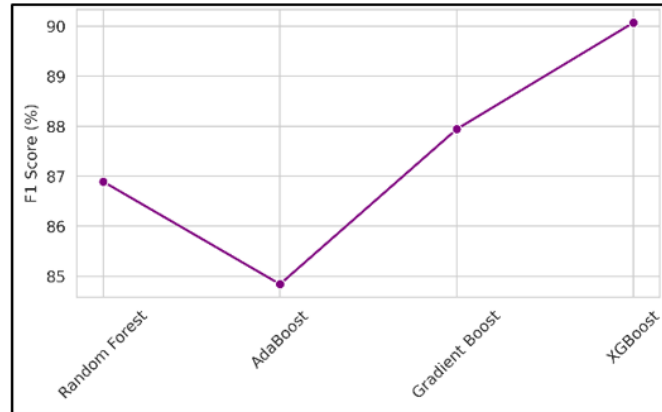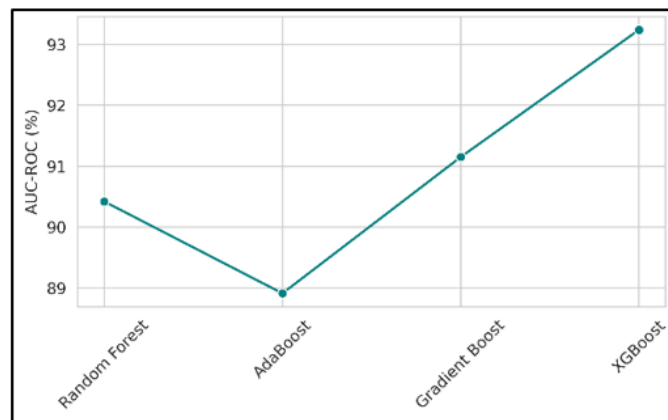
Figure 5

Figure 5 Comparison of Recall with Various Model

The number (5) is used to test the success of each model in identifying all the grads that can be hired. XGBoost has the best number of 89.77% which indicates that it is quite good at detecting true positives. The nearest one is Gradient Boost. AdaBoost and random forest possess a little less recall. The differences are more visible with the bright magma bars and it is evident that the models with boosting processes are more sensitive as compared to models with bagging processes.

Fiugre 6

Figure 6 Comparison of F1-Score with Various Model

Being a harmonic combination of precision and memory, the F1 score is represented in the Figure 6. XGBoost wins again with a score of 90.07, which indicates that it has the most appropriate balance between accuracy and memory. The gradual improvement of AdaBoost by XGBoost indicates that boosting algorithm is becoming more proficient at their tasks. The distinct marks and standard curves enable one to identify gaps on performance and trends within group models easily.

Figure 7

Figure 7 Comparison of AUC-ROC with Various Model

The Figure 7 indicates the ability of each model to distinguish between the capabilities of grads to secure jobs at the various levels and those unable to secure employment. XGBoost has the highest number of 93.24, indicating that it has a higher discriminative power. AdaBoost and Random Forest are slightly lagging behind and Gradient Boost is closely trailing it. The bright green smooth changes with smooth shifts are evidence of the high general classification capabilities of XGBoost, which captures the gradient of the quality predicted.

4. CONCLUSION

This paper demonstrated that ensemble learning can effectively forecast the capacity of a graduate to secure employment once various forms of data are incorporated including academic achievements, employment history, soft skills and resume connotations. Among all the ensemble models, which were considered, Extreme Gradient Boosting (XGBoost) performed best in all the significant evaluation metrics including accuracy, precision, recall, F1-score, and AUC-ROC. This performance stability indicates the performance of gradient-boosted systems in relation to various types of data which are only partially organised. A lot of feature engineering and dimensionality reduction was done to convert

the data into a format that could be more effectively recognized as a pattern. It was of great importance to add TF-IDF-based resume embeddings and measured soft skill measures since these were the most accurate ones. The traditional academic factors, however, are not as important as the other factors are observed to be. It is an indication that behaviour and practicality are becoming more relevant in employment determination. What is most useful about the model is that it can be explained and understood, in particular via SHAP analysis and scores on gain-based features enable us to understand things in a better way, as well as provide information we can apply. Through these lessons, schools may make more appropriate decisions when it comes to the way they can enhance their courses, conduct skill-building programs as well as provide career counselling services to enable graduates secure better jobs. The results and the methods presented there indicate that machine learning can serve not just a single purpose, such as forecasting the future of the labour force and interpreting the information regarding schools. Researchers can consider adding in the future real-time trends in the labour market, or the long-term success of students to increase the predictive capacity of the future and adapt to the altering job markets.

CONFLICT OF INTERESTS

None.

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None.

REFERENCES

Albina, A., and Sumagaysay, L. (2020). Employability Tracer Study of Information Technology Education Graduates from a State University in the Philippines. Social Sciences and Humanities Open, 100055, 1–6. https://doi.org/10.1016/j.ssaho.2020.100055

Assegie, T. A., Salau, A. O., Chhabra, G., Kaushik, K., and Braide, S. L. (2024). Evaluation of Random Forest and Support Vector Machine Models in Educational Data Mining. 2024 2nd International Conference on Advancement in Computation and Computer Technologies (InCACCT), 131–135. https://doi.org/10.1109/InCACCT61598.2024.10551110

Aviso, K., Janairo, J., Lucas, R., Promentilla, M., Yu, D., and Tan, R. (2020). Predicting Higher Education Outcomes with Hyperbox Machine Learning: What Factors Influence Graduate Employability? Chemical Engineering Transactions, 81, 679–684.

Celine, S., Dominic, M. M., and Devi, M. S. (2020). Logistic Regression for Employability Prediction. International Journal of Innovative Technology and Exploring Engineering, 9(3), 2471–2478. https://doi.org/10.35940/ijitee.C8170.019320

Chopra, A., and Saini, M. L. (2023). Comparison Study of Different Neural Network Models for Assessing Employability Skills of IT Graduates. 2023 International Conference on Sustainable Communication Networks and Application (ICSCNA), Theni, India, 189–194. https://doi.org/10.1109/ICSCNA58489.2023.10368605

Maaliw, R. R., Quing, K. A. C., Lagman, A. C., Ugalde, B. H., Ballera, M. A., and Ligayo, M. A. D. (2022). Employability Prediction of Engineering Graduates Using Ensemble Classification Modeling. 2022 Ieee 12th Annual Computing and Communication Workshop and Conference (CCWC), Las Vegas, NV, USA, 288–294. https://doi.org/10.1109/CCWC54503.2022.9720783

Monteiro, S., Almeida, L., Gomes, C., and Sinval, J. (2020). Employability Profiles of Higher Education Graduates: A Person-Oriented Approach. Studies in Higher Education, 1–14. https://doi.org/10.1080/03075079.2020.1761785

Nordin, N. I., Sobri, N. M., Ismail, N. A., Mahmud, M., and Alias, N. A. (2022). Modelling Graduate Unemployment from Students' Perspectives. Journal of Media and Communication Studies, 8(2), 68–78. https://doi.org/10.24191/jmcs.v8i2.6986

Oliver, N., Pérez-Cruz, F., Kramer, S., Read, J., and Lozano, J. (2021). Machine Learning and Knowledge Discovery in Databases. In Research Track 12975. Springer Nature. https://doi.org/10.1007/978-3-030-86523-8

Philippine Statistic Authority. (2021). Unemployment Rate in September 2021 is Estimated at 8.9 Percent.

Shahriyar, J., Ahmad, J. B., Zakaria, N. H., and Su, G. E. (2022). Enhancing Prediction of Employability of Students: Automated Machine Learning Approach. 2022 2nd International Conference on Intelligent Cybernetics

Technology and Applications (ICICyTA), Bandung, Indonesia, 87–92. https://doi.org/10.1109/ICICyTA57421.2022.10038231

Shuker, F. M., and Sadik, H. H. (2024). A Critical Review on Rural Youth Unemployment in Ethiopia. International Journal of Adolescence and Youth, 29(1), 1–17. https://doi.org/10.1080/02673843.2024.2322564

Tamene, E. H., Salau, A. O., Vats, S., Kaushik, K., Molla, T. L., and Tin, T. T. (2024). Predictive Analysis of Graduate Students' Employability Using Machine Learning Techniques. 2024 International Conference on Artificial Intelligence and Emerging Technology (Global AI Summit), Greater Noida, India, 557–562. https://doi.org/10.1109/GlobalAISummit62156.2024.10947923