DynaRank Predictor: Unravelling the Dynamics of Variations, Randomness, and Intricacy Metrics in University Rankings

Nidhi Agarwal[1] [0000-0002-9044-8989], Abhishek Raj Permani[2], Sudhir Kumar Tiwari[3], Sayan Kundu[4], Dhanush Chalicheemala[5], Charan Reddy Nandyala[6]

[1] School of Computing Science and Engineering, Galgotias University, Greater Noida, India, nidhiagarwal82@gmail.com
[2] Department of Artificial Intelligence and Data Science, Indian Institute of Technology, Patna, India
abhishekraj29011998@gmail.com
[3] Department of Artificial Intelligence and Data Science, Indian Institute of Technology, Patna, India
sudhiree023@gmail.com
[4] Department of Artificial Intelligence and Data Science, Indian Institute of Technology, Patna, India
sayandata555@gmail.com
[5] Department of Computational Data science, University of California, USA,
chalicheemala.dhanush@gmail.com
[6] Department of Computational Data science, University of California, USA, charanreddy671@gmail.com

Corresponding author- Nidhi Agarwal, nidhiagarwal82@gmail.com

Abstract

In the realm of higher education, predicting university rankings remains a critical endeavor with far-reaching implications for stakeholders ranging from students and faculty to policymakers and funding agencies. Traditional models often overlook the intricate interplay of fluctuations, noise, and complexity metrics within the network of universities, leading to limited predictive accuracy and robustness. In this research paper, a model DynaRank Predictor is proposed, which harnesses the dynamic nature of university networks to enhance ranking predictions. The DynaRank Predictor integrates three key components – Analysis of Network Dynamics, Incorporation of Fluctuation, Noise and Integration of Complexity Metrics. Network Dynamics Analysis leverages state-of-the-art network analysis techniques, captures the evolving relationships and interactions among universities thus unveiling hidden patterns and structures within the network. Fluctuation and Noise Incorporation accounts explicitly for fluctuations and noise stemming from various factors such as research output variability and funding fluctuations. It lets the proposed model mitigate the impact of uncertainty on ranking predictions, ensuring more reliable outcomes. This is the first work in which dynamic analysis is done for such problems. Complexity Metrics Integration incorporates a rich array of complexity metrics derived from network theory, including centrality measures, clustering coefficients and diversity indices, to capture the multidimensional nature of university networks and inform the prediction process. Through extensive empirical evaluations on comprehensive university ranking datasets, the superior predictive performance and accuracy of the DynaRank Predictor is ascertained as compared to existing models. The model not only achieves higher accuracy in ranking predictions but also provides valuable insights into the underlying dynamics and drivers of university rankings. The DynaRank Predictor offers a versatile framework adaptable to diverse ranking scenarios and scalable to accommodate evolving network dynamics and data sources. Thus, the DynaRank Predictor represents a paradigm shift in university ranking prediction, offering a holistic approach that embraces the complexity and dynamics inherent in university networks. By unlocking the predictive power of network dynamics while effectively addressing fluctuations, noise, and complexity, the model opens new avenues for advancing our understanding of academic ecosystems and facilitating informed decision-making in higher education.

Keywords: network dynamics analysis; fluctuation and noise incorporation; complexity metrics integration; university ranking prediction; higher education.

1. Introduction

University rankings, often touted as a guiding light for students, faculty, and policymakers alike, suffer from a fundamental flaw: they paint a static picture of a dynamic system. These rankings typically rely on a narrow set of metrics, like research output or faculty reputation, neglecting crucial aspects for students like teaching quality, campus culture, and affordability. Additionally, rankings present a snapshot in time, failing to capture the ever-evolving nature of universities. A rising young institution with a focus on innovation might be overshadowed by established names, simply because of a lack of historical prestige. Finally, external factors like funding fluctuations or changes in leadership can significantly impact a university's performance, introducing "noise" that traditional rankings don't account for. It might happen that a university with a strong research focus might rank highly, but its undergraduate teaching might be subpar. A dynamic ranking system would reveal this nuance. Similarly, a new university pioneering a revolutionary approach to education might not even appear on rankings because of its lack of historical data. Furthermore, a temporary decline in a university's performance due to funding cuts wouldn't be reflected in a static ranking. Thus, this research paper proposes the DynaRank Predictor, a novel model designed to address these limitations. DynaRank goes beyond the limited scope of traditional rankings by incorporating a broader set of factors. It considers student satisfaction, faculty-to-student ratio, and alumni career success alongside research and reputation. Moreover, it utilizes historical data and trends to predict future performance, providing a more comprehensive picture. DynaRank factors in external influences, modeling fluctuations and "noise" to create a robust prediction. The benefits of the proposed model are multifold. The stakeholders can benefit substantially. Students can make informed decisions about universities that truly align with their academic and personal needs. Faculty gains a clearer understanding of how their institution compares dynamically to others in their field. Policymakers can leverage data-driven insights to allocate resources effectively and support promising universities. Finally, funding agencies can invest in institutions with the greatest potential for impactful outcomes. However, creating a truly valuable tool requires careful consideration. Ensuring DynaRank incorporates relevant and unbiased data sources is crucial. Additionally, making the model accessible and understandable to different stakeholders, from students to policymakers, is essential for widespread adoption. Finally, a discussion around the potential impact on university behavior is necessary. By addressing the limitations of traditional rankings and incorporating the dynamic nature of universities, the DynaRank Predictor has the potential to revolutionize how we navigate the complex landscape of higher education.

1.1 Network Dynamics Analysis

Traditional university ranking methods treat universities like isolated islands, failing to consider the vibrant network of interactions and collaborations that define academia [1, 2]. The DynaRank Predictor addresses this shortcoming with a powerful framework for network dynamics analysis. This framework goes beyond static data points to capture the ever-evolving landscape of university connections. One technique involves analyzing co-authorship data. Here, connections are formed between universities based on how often faculty co-author research papers. By studying how these networks evolve over time, DynaRank can identify emerging research clusters and collaborations. This can signal rising stars in specific fields, allowing the model to predict which universities are likely to climb the rankings in the future. Another approach involves mapping the flow of knowledge between universities. This is achieved by tracking student and faculty mobility. Universities that attract top researchers and students from prestigious institutions will see a rise in their network centrality. This indicates a potential future rise in rankings, as these institutions become hubs of knowledge and innovation. Citation patterns offer another valuable lens. DynaRank can analyze these patterns to identify universities with highly influential research. By examining how citation flows change over time, the model can predict which universities are gaining traction and influencing future research directions. These are strong indicators of a potential rise in future rankings. To translate these network dynamics into concrete insights, DynaRank Predictor utilizes advanced network metrics. Metrics like betweenness centrality and clustering coefficient help quantify a university's position and interconnectedness within the academic network. By analyzing how these metrics change over time, the model can predict how a university's influence and collaboration patterns might evolve, impacting their future standing in the rankings. Furthermore, DynaRank integrates machine learning algorithms to analyze historical ranking data alongside network dynamics. This allows the model to identify patterns in ranking fluctuations caused by external factors like funding changes or leadership transitions. By factoring in these patterns, DynaRank can provide more robust and noise-resistant predictions. Network analysis also allows DynaRank to identify communities within the academic network. These communities group universities with similar research focus, teaching styles, or geographical location. By analyzing the performance trends within these communities, DynaRank can predict how individual universities might fare compared to their peers. In essence, DynaRank Predictor moves beyond static snapshots of universities. It harnesses the power of network analysis to capture the dynamic flow of knowledge and interactions that shape the academic world. By considering these network dynamics alongside traditional ranking metrics, DynaRank aims to provide a more comprehensive and predictive understanding of university performance, empowering stakeholders to navigate the complex landscape of higher education.

1.2. Fluctuation and Noise Incorporation

University rankings, often touted as a guiding light for students, faculty, and policymakers alike, suffer from a fundamental flaw: they paint a static picture of a dynamic system. These rankings typically rely on a narrow set of metrics, like research output or faculty reputation, neglecting crucial aspects for students like teaching quality, campus culture, and affordability. Additionally, rankings present a snapshot in time, failing to capture the ever-evolving nature of universities. A rising young institution with a focus on innovation might be overshadowed by established names, simply because of a lack of historical prestige. Finally, external factors like funding fluctuations or changes in leadership can significantly impact a university's performance, introducing "noise" that traditional rankings don't account for. Consider this: a university with a strong research focus might rank highly, but its undergraduate teaching might be subpar. A dynamic ranking system would reveal this nuance. Similarly, a new university pioneering a revolutionary approach to education might not even appear on rankings because of its lack of historical data. Furthermore, a temporary decline in a university's performance due to funding cuts wouldn't be reflected in a static ranking. Enter the DynaRank Predictor, a novel model designed to address these limitations. DynaRank goes beyond the limited scope of traditional rankings by incorporating a broader set of factors. It considers student satisfaction, faculty-to-student ratio, and alumni career success alongside research and reputation. Moreover, it utilizes historical data and trends to predict future performance, providing a more comprehensive picture. Perhaps most importantly, DynaRank factors in external influences, modeling fluctuations and "noise" to create a robust prediction. The benefits for stakeholders are substantial. Students can make informed decisions about universities that truly align with their academic and personal needs. Faculty gains a clearer understanding of how their institution compares dynamically to others in their field. Policymakers can leverage data-driven insights to allocate resources effectively and support promising universities [3]. Finally, funding agencies can invest in institutions with the greatest potential for impactful outcomes [4, 5]. However, creating a truly valuable tool requires careful consideration. Ensuring DynaRank incorporates relevant and unbiased data sources is crucial. Additionally, making the model accessible and understandable to different stakeholders, from students to policymakers, is essential for widespread adoption. Finally, a discussion around the potential impact on university behavior is necessary. Will a dynamic ranking system foster more competition or collaboration between institutions? By addressing the limitations of traditional rankings and incorporating the dynamic nature of universities, the DynaRank Predictor has the potential to revolutionize how we navigate the complex landscape of higher education.

1.3. Complexity Metrics Integration

Traditional university ranking methods suffer from a one-dimensional view, treating universities like isolated entities with static qualities. This approach fails to capture the intricate web of interactions and collaborations that define academia. The DynaRank Predictor addresses this limitation by integrating not only network dynamics analysis but also a diverse array of complexity metrics derived from network theory. These complexity metrics offer a multifaceted view of university networks, going beyond the simplistic measures used in traditional rankings. DynaRank leverages complexity to provide a more comprehensive picture in several ways. Firstly, it analyzes universities through the lens of "small-world networks" – surprisingly interconnected networks where seemingly distant institutions can be connected through a few short steps. By measuring these properties, DynaRank can identify universities well-positioned to leverage connections and knowledge across diverse fields, potentially leading to breakthroughs and higher rankings. Secondly, DynaRank examines modularity and clustering. Universities with similar research focus or teaching philosophies often form clusters within the network. By quantifying the strength of these clusters and analyzing changes over time, the model can predict how collaboration patterns might evolve, impacting universities' positions within their respective clusters and potentially influencing future rankings. Thirdly, DynaRank analyzes assortative, which measures the tendency for universities with similar characteristics to connect. For example, universities with high research output might be more likely to collaborate with each other. By analyzing assortative patterns, DynaRank can predict how external factors, like increased funding for specific research areas, might influence collaboration patterns and ultimately impact rankings. To translate these network complexities into enhanced predictions, DynaRank employs several solutions. Machine learning algorithms are integrated with complex metrics to identify hidden patterns and relationships within the network data, leading to more nuanced and accurate ranking predictions [6]. Additionally, complexity metrics are incorporated into network models to predict how the entire university network might evolve over time. This allows stakeholders to anticipate potential shifts in the landscape, such as the rise of new research powerhouses or the decline of established institutions due to changing collaboration patterns [7]. Finally, the model's ability to predict network evolution empowers stakeholders with the ability to benchmark universities against their likely future positions. Scenario planning based on different funding allocations or policy changes can also be performed using DynaRank, allowing for a more proactive approach to navigating the complexities of higher education. In essence, DynaRank Predictor moves beyond simplistic metrics and static snapshots. By embracing network dynamics and the power of complexity theory, the model offers a multi-faceted view of university networks. This comprehensive understanding allows DynaRank to provide more accurate and insightful ranking predictions, empowering stakeholders to make informed decisions in the ever-evolving world of higher education.

Research Questions

How can a dynamic, multi-factor model like DynaRank better predict future university performance compared to static, metric-limited rankings?

Which network dynamics—co-authorship, mobility, and citations—most strongly anticipate near-term and medium-term ranking shifts?

How do external fluctuations, including funding shocks and leadership transitions, propagate through academic networks to affect ranking trajectories?

To what extent do complexity metrics—small-world properties, modularity, and assortativity—improve predictive accuracy and robustness?

What trade-offs emerge between prediction accuracy, interpretability, and fairness when integrating heterogeneous data sources?

Objectives and Motivation of The Study

Design and implement the DynaRank Predictor that integrates network dynamics, fluctuation modeling, and complexity metrics.

Construct a comprehensive, bias-aware data pipeline spanning research, teaching, satisfaction, affordability, and mobility indicators.

Develop and evaluate forecasting models that leverage temporal trends and exogenous shocks for robust, noise-resistant predictions.

Quantify the incremental value of network and complexity features over traditional baselines using rigorous, reproducible experiments.

Produce stakeholder-facing explanations and visual diagnostics to enhance transparency, usability, and policy relevance.

The paper is organized into 6 sections, where section 2 highlights the work done by various researchers in this field. It follows section 3 which describes the methodology being proposed in detail. Section 4 describes the various empirical evaluations and results. It is followed by section 5 which compares the proposed model with various similar existing models based on suitable metrics. Section 6 finally concludes the paper with future work and limitations of the existing work.

2 Related Work

Today "academic industry" is driven by a major factor called "ranking" which holds an institute's reputation in the national and international market. A lot of efforts are being made by the researcher community to predict their ranks in advance so that they can take various corrective and preventive measures in advance. An effort was done by [8] where the experts used a comparatively new MADM (Multi Attribute Decision Making) approach called MULTIMOORA to derive the rankings of 26 famous international level universities of China. The MULTIMOORA method was enhanced using Borda rule to generate better results. It was the first introduction of MULTIMOORA extension using combined weights for ranking universities. Multiple quality attributes with varying levels of importance (weights) were considered. For the first time, many famous universities i.e. 26 of China were ranked based on the selected attributes with their pre-specified weightage. This work contributed to a more accurate and steady assessment of various attributes pertaining to academic quality attributes.

A technique known as "Webometrics" has played a prominent role in various studies. It uses four sub-attributes which are elaborated as: how an academia presents itself on internet, how it is already visible on internet, how much it is open and how much it is excellent globally. All these sub-attributes are calculated empirically. The basis of the methodology is to improve the above-said sub-attributes to improve the overall rankings. In [9], the researchers used webometrics as a tool for ranking the universities by taking example of oncology domain. The novelty of this approach lies in its special application of bibliometric attributes in the oncology domain to rank the universities. It considered a varied set of performance indicators. The work provides insightful findings regarding various factors contributing to bibliometric ranks for oncology-based universities. The study concluded that bigger, specialization-based and research-oriented universities gained higher bibliometric scores as compared to their counterparts because of higher publication outputs. The quality of data and information for generating rankings played a significant role in influencing their outcomes. If some significant data is missed from weblinks, then it would influence the ranks. The study assessed the HEIs in a deeper holistic way across various parameters like research output, citation impact, collaboration networks, and international reach for their overall research performance. The study let researchers conclude that webometrics ranks must not be considered as absolute measures of university quality, but rather as one of the tools for informed decision-making.

The authors in [10] provided a massive overview of webometrics and its detailed methodology. It is the first work which reviewed the advantages of webometrics to a humongous level especially for underdeveloped and developing countries. Though the study doesn't provide any experimental outputs unlike in other studies. Rather it presents many empirical outputs based on webometrics ranking system. It highlights the importance of methodology for all types of universities. It provides important understanding regarding webometrics to all researchers and stakeholders for evaluating academic performance. The study concludes that Webometrics ranking system can prove to be an important tool support for comparing the web-presence and visibility of any academia involved in HEIs. universities and research institutions. However, it is important to use these rankings with caution and to be aware of their limitations. The study's findings can help to improve the accuracy and fairness of Webometrics rankings and make them a more reliable tool for evaluation and benchmarking.

In [11], researchers adopted "webometrics" in their research work by considering it "as an important contributor for quality higher education" for various Kenya based academic institutions. It was the first work in which focus was laid on the educational quality and research for Kenian universities. It contributed significant work for quality analysis and its improvement of all academic settings in Kenian universities. The study used a mixed-method approach, combining quantitative and qualitative data. The quantitative data consisted of Webometrics ranking data for Kenyan universities. The qualitative data consisted of interviews with university administrators and faculty members. It found a positive correlation between Webometrics ranking and quality education including research for Kenian universities. It found that academia with higher Webometrics ranks bear much improved research outputs with enhanced quality of teaching and pupil engagement. The study also concluded that academic collaborations and partnerships should be encouraged to higher ranks and improved performance for academic settings. These can be at both national and international levels. Other strategies that were found to be effective for improving Webometrics rankings include: Using web champions, Marketing and awareness developing a strong online presence, creating high-quality content, Promoting the institution's research. The study bore many implications for academicians and others related to Kenya based academia. It served as an important insight for decision makers to take funding related decisions for the for the development of higher education in Kenya. The higher academicians got an opportunity to identify areas of improvement and thus improve their policies and strategies. Finally, the study recommended that if Kenyan universities would continue to invest in their web presence and develop policies and strategies for improving their Webometrics rankings, then this could help to raise their profile and attract more students, faculty, staff and research funding.

The researchers in [12] conducted a deep comparative study of national and international ranking systems based on their attributes, weightage and rank results. It was the first study which compared both the categories of rankings to such a deep extent. It drew upon a comprehensive data set and identified key patterns and trends for both types of ranking systems. This study led to a deeper understanding of the influence, importance, relevance of various parameters and their sub parameters pertaining to both the types of ranking systems It was found that the national ranking parameters focus majorly on academic, institution related attributes while the international ones focus majorly on research-oriented attributes. Thus, global ones emphasize more research output with publications in high quality journals. The national ones, on the contrary, focus more on publication in local journals, quality of teaching, pupil and employer satisfaction. The study finds that global rankings are more susceptible to manipulation as they have the flexibility to influence research output as compared to factors pertaining to national rankings. The national parameters provide a more comprehensive assessment of research performance within the national context. The study proved to be very important as it provided valuable insights for researchers, policymakers, and university officials who rely on university rankings for informed decision-making. It emphasizes the importance of considering the strengths and limitations of both global and national rankings when evaluating institutional performance. Thus, the study concluded that both the types of ranking systems were important. Both have their own applicability in their respective domains. But understanding both their limitations and offerings is imperative for informed decision-making and efficient benchmarking of institutional performance.

Another study [13] evaluates the websites of agriculture-based universities for Maharashtra state. It was first effort to rank and evaluate the performance of agriculture universities for a particular state in India. It provides an in-depth analysis of the online webometrics presence of Maharashtrian domain important for agriculture-based universities. The study finds differences in terms of webometrics performance among five such universities. The size of university, quality of data, timely feeding, updating and maintenance or records at university websites proved as essential parameters. The study employed a range of webometric indicators, including Alexa Rank, Google PageRank, MozRank, Majestic SEO Domain Authority, and Majestic SEO Citation Flow to assess the universities' website performance. The findings provide valuable insights for agricultural universities in Maharashtra to enhance their online presence and effectively disseminate their research and educational resources. The work identifies a particular university in the state, Dr. Punjabrao Deshmukh Krishi Vidyapeeth's website is performing better than its counterparts based on a particular ranking factor "bounce rate". The study concludes that Webometric analysis can prove as an imperative tool for agriculture based HEIs to evaluate their online presence and identify areas for improvement. By leveraging webometric data, the academia can elevate their visibility, attract potential students and researchers, and strengthen their position in the global agricultural research landscape.

Researchers in [14] proposed a novel tool-support for privately owned educational institutions of China for enhancing their marks and subsequent ranks based on core competence attributes. It was the first work to introduce a "Balanced Scorecard framework" for this purpose. An evaluation system to judge the performance of institutions was developed considering all major parameters which can affect ranks of any academia. Overall, the novelty lies in the development of a performance evaluation system that is specifically designed for private higher education institutions in China, using the "Balanced Scorecard Framework" and the practical implications and insights gained from its implementation in this context. The study finds the effectiveness of such a system in elevating the core competencies and promoting the holistic development of these institutions. The study highlights the unavailability of a comprehensive evaluation system which can cater to the requirements of privately owned HEIs of China. While the study does not present experimental output in the traditional sense, it provides empirical evidence from real-world implementation cases, demonstrating the practical applicability of the proposed system. Thus, the study successfully demonstrates the utility of the balanced scorecard in evaluating the performance of private higher education institutions in China, offering a valuable tool for policymakers, administrators, and stakeholders involved in this sector.

Another significant work was proposed by [15] in the form of a tool-support for self-assessment. It was the first piece of work, based on self-assessment, to show how well a particular academia manages to attain its own learning outcomes. The study focusses majorly on undergraduate engineering study. The work included an exhaustive analysis of academic aspects for undergraduate engineering projects, highlighting the major learning outcomes and assessment methodologies. The authors' findings helped greatly to understand student engagement and knowledge acquisition through curriculum related projects. This work helped professionals as well as students in evaluating and generating their work ethically and self-assessed manners. The significance of this study lies in its potential to enhance pedagogical approaches within engineering education. By providing insights into effective learning outcomes and assessment strategies, the research offers valuable guidance for educators and institutions aiming to optimize the educational experience for engineering students. The experimental output of the study involves a detailed analysis of the learning outcomes achieved by students participating in an undergraduate engineering project, coupled with an examination of the assessment methods employed. The conclusions drawn from the research highlight the importance of aligning project-based learning with well-defined learning outcomes and appropriate assessment methodologies. The findings underscore the need for a thoughtful integration of theory and practice in engineering education, emphasizing the role of projects in fostering meaningful learning experiences. Ultimately, this study contributes to the ongoing discourse on pedagogical advancements in engineering education, offering practical insights for educators and stakeholders striving to enhance the academic journey of undergraduate engineering students.

In another work, [16] suggested academia accolades as an important score judgement criteria for any institution. The authors emphasize highly important "international academic awards" with their impact on "university rankings" as a part of "Quantitative Science Studies". Researchers focused on major university world ranking frameworks using survey-based information for majorly Cited Researchers for identifying the top hundred most prestigious academia awards. The experimental setup involved using statistical methods for quantitative analysis for assessing the correlations of "international academic awards" with "university rankings". The work was quite significant and unique as it laid major focus on "majorly Cited researchers", which bears high contribution when ranking any academia. This correlation was not emphasized by other researchers till then. The work offers valuable insights for academia aiming to improve their international recognition. Thus, the work significantly contributes to the contributing factors for improved "university rankings". It offers a data centric approach for highlighting the above-mentioned correlation.

In [17] another contributory work was proposed in this direction by taking a set of dominant ranking indicators to help universities predict and improve their ranking strategies. Researchers used the predictive method to find the correlations among four academic ranking systems for year 2018 –ARWU, THE, QS and URAP. Different weightage values to analyze the number of contributions of these parameters were also suggested. It was the first work to consider the parameters of all the four major international ranking parameters together. The methodology was novel to better understand academic dynamics especially for engineering-based curriculum. It provided better in-depth analysis and learning outcomes in the form of case studies and practical based engineering projects. It was the first work which could provide strong correlation between specific project components and the attainment of educational objectives. Thus, this study could address the important gap which was existing in the state-of-art till then by providing this correlation in detail for undergraduate engineering program. Thus, the work concluded that project designing based on proper learning objectives and using proper assessment tools could measure the attainment of desired skills and knowledge more accurately. By narrowing the gaps between theory and practice, the work supported a pedagogical approach which could maximize the academic impact on engineering projects. The work could, thus, provide valuable insights to educationalists, curriculum designers, and other senior academicians who longed to enhance the efficacy of undergraduate engineering education using properly defined learning outcomes and appropriate assessment tools.

In another study [18], researchers present a novel methodology for enhancing the quality assurance ways for any academia involved in higher education by applying the data mining concepts. The work involves a novel approach of hybridization of data mining approaches with the accreditation processes. It could offer a unique way for gaining better insights for assessing and ranking academia with respect to accreditation related data. The experimental output involves the application of data mining algorithms to real-world data from higher educational institutions, demonstrating the feasibility and efficacy of the proposed approach. The study concludes that integrating data mining into quality assurance processes can lead to more robust and transparent assessments, ultimately contributing to the continuous enhancement of educational standards. The work highlighted the efficacy of data mining techniques to identify the main performance indicators and trends contributing towards the overall education quality of HEIs. The study reveals the fact that by adopting data-driven methods, the academicians would be able to gain valuable insights of the factors which can influence accreditation and rankings. But it needs a sound knowledge of the various factors contributing to the same. The work is significant as it holds the potential for revolutionizing evaluation and improved methodologies for any academic involved in higher education. Thus, the study could offer a more objective and informed basis for accreditation and ranking decisions. This research not only advances the field of accreditation but also holds implications for policymakers, administrators, and educators seeking data-driven strategies to ensure and improve the quality of higher education institutions.

Researchers in [19] have done a significant amount of work for rank prediction at international level using machine learning. The novelty of their work lies in adoption of machine learning techniques for predicting the global university rankings. All the performance indicators contributing to global rankings were considered in this work. The dataset involved Times Higher Education World University Rankings which comprises of global performance indicators for evaluating the performance of any academia. The data was analyzed in various steps. The first step involved analyzing ranking data at country level to find the variations for performance indicators and thus selecting the dominating factors. The next step involves prediction of ranks for upcoming year based on previous years rank scores which are generated in previous step. Only influential factors were considered for rank predictions using this two-step method using outlier detection and rank score calculation algorithms. Then, at the third step, the universities were ranked globally using THE ranking system. The accuracy of the predictive system was calculated using recall, number of matched ranks and ROC curve with respect to the rank deviation. The experimental results demonstrate that the proposed university rank prediction system is acceptable to estimate upcoming global university rankings with good accuracy value.

In another significant work in [20], a data-driven decision-making model was proposed using machine learning for academia involved in higher education. Thus, artificial intelligence was used and machine learning to develop a novel model for decision making for colleges and universities. They have thoroughly analyzed humongous students' related data, graduates' curriculum data-rate and curriculum design to take various administration related decisions in academia using machine learning techniques. They suggested and adopted all the measures to improve the academics at the higher educational level.

3 Proposed Methodology

The methodology employed in developing the DynaRank Predictor, as depicted in Figure 1. encompasses three stages, each tailored to capture different aspects of the dynamic interplay within university networks. Data collection and preprocessing are conducted to gather comprehensive information on university attributes, connectivity patterns, historical ranking data, research output, funding allocations, and other relevant factors. This process involves compiling data from diverse sources, including academic databases, university websites, research publications, and funding agencies [21].

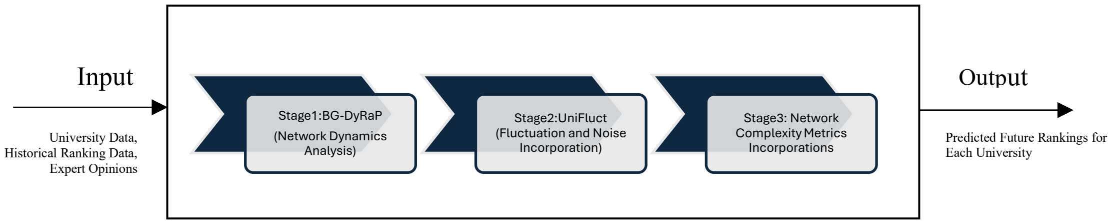

Figure 1. Proposed Model "DynaRank Predictor".

The first stage involves network dynamics analysis techniques, including temporal analysis and community detection algorithms, which are applied to uncover evolving relationships and structures within the network. Incorporating graph-based models and Bayesian methods into DynaRank Predictor offers significant advantages. This will enhance the model's ability to capture the dynamic nature of academia and provide stakeholders with valuable insights for navigating the ever-evolving landscape of higher education. This step involves leveraging advanced computational methods to extract meaningful insights from large-scale network data. By analyzing the temporal evolution of connectivity patterns and identifying communities or clusters of universities with similar characteristics, the model gains

Algorithm 1 DynaRank Predictor Algorithm

Input:

- Dataset D containing data points (items, datasets, etc.)
- Centrality metrics: Betweenness Centrality (BC), Closeness Centrality (CC), Clustering Coefficient (Cp), Herfindahl Index (HI)
- Ground truth values (Y) for a subset of data points in D (optional)

Output:

- Ranked list of data points in dataset D

Variables and Ranges:

- **centrality_score(d, M):** Function that calculates the centrality score for data point d using metric M (BC, CC, Cp, HI). Range: Specific to each metric ([0, 1] for BC, CC; [0, infinity] for HI).
- **initial_rank(d):** Function that assigns an initial ranking position to data point d based on a baseline criteria (e.g., data quality, domain relevance). Range: Integer representing position in the initial ranking (1 being the highest).
- **connection_strength(d1, d2):** Function that defines the strength of the connection between data points d1 and d2. Range: [0, 1] (higher values indicate stronger connection). Factors like domain similarity, co-occurrence, or user-defined metrics can be used.
- **alpha:** Weighting parameter for the combined centrality score (0 to 1). Controls the influence of centrality on the final ranking.
- **beta:** Weighting parameter for MAPE (0 to 1). Controls the influence of MAPE on the final ranking (applicable only if ground truth values are available). Range: [0, 1].
- **MAPE(d):** Function that calculates the Mean Absolute Percentage Error between the predicted value for data point d and its corresponding ground truth value (Y) if available. Range: [0, infinity] (lower values indicate better prediction accuracy).

Steps:

1. **Centrality Calculation:**

   For each data point d in D, calculate its centrality score for each chosen metric M (BC, CC, Cp, HI) using the centrality_score(d, M) function.

2. **Initial Ranking:**

   Create an initial ranking of data points based on the initial_rank(d) function.

3. **DynaRank Iteration (Multi-Centrality):**

```
current_metric_index = 0  # Index for centrality metric
centrality_metrics_length = len(centrality_metrics)  # Number of centrality metrics
while current_metric_index < centrality_metrics_length:
    current_metric = centrality_metrics[current_metric_index]  # Get current metric
    for data_point in dataset:
        neighbors = get_neighbors(data_point)  # Implement function to find connected    data points
        # Calculate weighted average centrality score (WACS)
        wacs = alpha * data_point.centrality_scores[current_metric]
        for neighbor in neighbors:
            wacs += (1 - alpha) * connection_strength(data_point, neighbor) * neighbor.centrality_scores[current_metric] / len(neighbors)
        # Update ranking position
        adjusted_rank = (1 - beta) * data_point.rank
        # If ground truth values available for d:
        if ground_truth and data_point in ground_truth:
            adjusted_rank += beta * (wacs + (1 - wacs) * (1 - mape(data_point) / max(mape(d) for d in dataset if mape(d))))
        # Else: (no ground truth)
        else:
            adjusted_rank += beta * wacs
        data_point.rank = adjusted_rank
    current_metric_index += 1  # Move to next metric


4. # Final Ranking Combination:
ranked_data = sorted(dataset, key=lambda d: d.rank)  # Sort data points based on final rank
# Output: ranked_data contains the ranked list of data points
```

gains deeper insight into the underlying dynamics driving fluctuations in rankings. Following network dynamics analysis, the model incorporates fluctuations and noise into the prediction framework. This involves the development of probabilistic models to quantify the uncertainty introduced by fluctuations in university attributes and external factors. By explicitly accounting for fluctuations and noise, the DynaRank Predictor produces more reliable ranking predictions that are robust to variations in the underlying data. Various statistical and machine learning techniques, such as time series analysis, stochastic modeling, and ensemble learning, are employed to model and mitigate the impact of fluctuations and noise on ranking predictions [22–25].

Finally, complexity metrics derived from network theory are integrated into the prediction process to provide a holistic understanding of university networks. These metrics, including centrality measures, clustering coefficients, and diversity indices, offer valuable insights into the structural properties of the network and the roles played by individual universities within it. By incorporating these metrics into the prediction framework, the DynaRank Predictor enhances the accuracy and depth of ranking predictions, empowering stakeholders with actionable insights for decision-making [26–30].

3.1. Stage 1: BG-DyRaP (Bayesian Graph-Integrated Dynamic Ranking Predictor) - Network Dynamics Analysis

The DynaRank Predictor has a strong foundation for dynamic university ranking prediction using network analysis. A novel hybridized model Bayesian Graph-Integrated Dynamic Ranking Predictor (BG-DyRaP) is proposed at the first stage of the proposed model by integrating Graph-based algorithms with Bayesian methods at the first stage for improved network representation and efficient rank predictions. This is depicted using Figure 2.

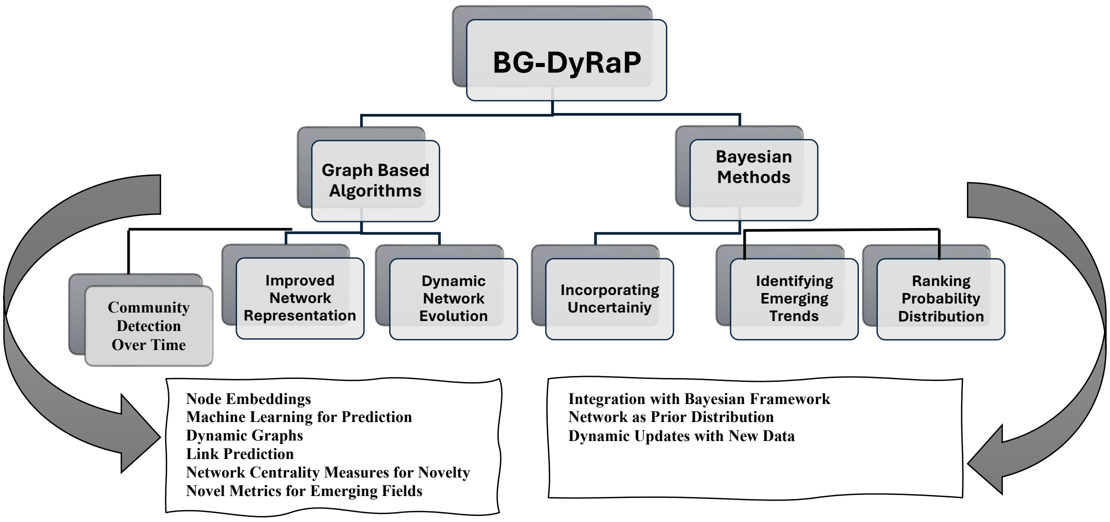

Figure 2. Hybridized Model BG-DyRaP for Stage 1

The universities are represented as numerical vectors called embeddings, based on their network position and connections. DeepWalk technique is used to capture complex relationships within the network. A machine learning model based on Gradient Boosting is selected for prediction. It is first trained on historical ranking data and the node embeddings. Thus, the model learns to predict future rankings based on the network dynamics encoded in the embeddings. For dynamic analysis, a series of graphs is constructed representing the academic network at different points in time [31]. This captures the evolution of collaborations, citations, and faculty/student mobility. Communities are then identified within the network for each period. These communities are then tracked over time to see how they evolve and how individual universities move between them. This helps in identifying universities entering or exiting high-performing communities, indicating potential ranking changes. Linked predictions are then made using network analysis techniques to predict future collaborations, citations, or faculty movements. This information is then fed into the ranking prediction model to improve its ability to anticipate future changes.

This allows the Bayesian model to continuously refine its predictions based on the evolving network dynamics. By combining the strengths of both methods, DynaRank can provide more accurate and reliable predictions of future university rankings. Graph-based models can identify communities within the network[32, 33] [34–39]. Analyzing performance trends within these communities allows for more nuanced predictions for individual universities compared to just looking at overall network position. Thus, one can explicitly represent universities as nodes and interactions (co-authorship, faculty/student mobility, citations) as edges. This allows DynaRank to capture complex relationships beyond simple pairwise comparisons. Dynamic network evolution analyzes how the network structure evolves over time. This helps identify rising research clusters, key influencers, and universities experiencing significant network growth, which are all crucial for predicting future rankings. Ranking data often has inherent uncertainties. Bayesian methods can account for this by using prior knowledge (historical rankings, expert opinions) and updating predictions as new data like recent research outputs, faculty changes etc. becomes available. This leads to more robust and adaptable predictions. Bayesian techniques excel at identifying trends in data with inherent noise. They can help DynaRank distinguish between short-term fluctuations and long-term trends in network dynamics that can significantly impact future rankings. Instead of a single point prediction, Bayesian methods can provide a probability distribution for a university's future ranking position. This gives stakeholders a clearer understanding of the range of potential outcomes and the associated level of confidence [40]. Thus, the proposed network structure at stage-1 using BG-DyRaP supports prior distribution in the Bayesian framework, leading to more accurate predictions that capture the dynamic nature of university interactions.

3.2. Stage 2: - UniFluct (University Fluctuation and Noise Integrated Ranking) Fluctuation and Noise Incorporation

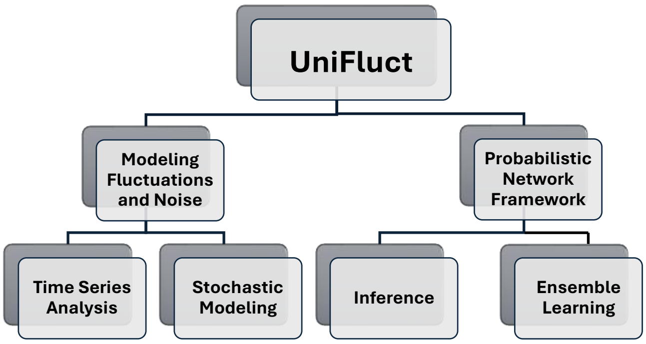

Figure 3. Model UniFluct for Stage 2

DynaRank takes a significant step forward as Stage 2 by incorporating fluctuations and noise into its prediction framework using UniFluct. This enhanced model leverages network analysis, probabilistic models, and various statistical and machine learning techniques to achieve more realistic and reliable university ranking predictions. The process begins with data preprocessing and feature engineering. Network metrics like betweenness centrality and clustering coefficient are calculated for each university at regular intervals, capturing the dynamic nature of their positions within the academic network. Additionally, data on university attributes such as publications, citations, and faculty mobility are collected, with statistical methods utilized to identify significant trends and potential outliers. To model these fluctuations and noise, UniFluct employs two key approaches. First, time series analysis techniques like ARIMA is used to forecast future values of network metrics based on historical trends. Confidence intervals are then incorporated to quantify the uncertainty surrounding these forecasts, acknowledging the inherent variability in university performance over time. Second, stochastic modeling is employed to represent the inherent randomness in university attributes. For instance, publication counts are modeled using Poisson distribution, while network metrics are treated as random variables with associated probability distributions.

Building upon these foundations, UniFluct constructs a Bayesian network. This network represents the relationships between university attributes (publications, citations), network metrics (betweenness centrality), and future ranking positions [41–43]. Conditional probability distributions are then encoded within the network, reflecting the influence of various factors on a university's ranking. For example, a high future ranking might be more likely for universities with a combination of strong publication output, prominent network positions, and recent faculty acquisitions. Bayesian inference algorithms are then used to continuously update the network's probability distributions as new data becomes available, allowing the model to adapt and refine predictions based on the latest information.

Finally, UniFluct utilizes machine learning with ensemble methods to further enhance its robustness. Multiple models, such as Random Forest or Gradient Boosting, are trained on historical ranking data alongside network metrics, time series forecasts, and university attribute data. By combining predictions from these models using bagging technique [44], UniFluct achieves greater resilience to noise and outliers compared to relying on a single model. Additionally, some ensemble methods provide estimates of prediction uncertainty, offering valuable insights into the range of potential future rankings due to inherent fluctuations.

This enhanced UniFluct framework offers several key benefits. By considering fluctuations and noise, the model generates more realistic ranking predictions that acknowledge the dynamic nature of academia. Probabilistic models and ensemble methods provide a measure of uncertainty, leading to more reliable predictions [22, 45, 46]. Additionally, the model's adaptability allows for continuous improvement as new data is integrated. Overall, incorporating fluctuations and noise using probabilistic models and various statistical and machine learning techniques significantly enhances DynaRank's ability to navigate the complexities of university ranking predictions. This allows for more realistic, reliable, and adaptable ranking forecasts, providing valuable insights for stakeholders within the academic landscape.

3.3. Stage 3: - Network Complexity Metrics Incorporation

DynaRank's prediction framework takes a significant leap forward by incorporating network complexity metrics alongside fluctuations and noise. These metrics, derived from network theory, offer valuable insights into the structural properties of the academic network and the roles played by individual universities within it. This section details the third stage of the proposed model where assessment metrics, their technical aspects, and hypothetical values suitable for it are applied. The three metrics Betweenness Centrality (*BtCen*), Closeness Centrality (*ClCen*), Clustering Coefficient (*ClCoeff*) are applied as Network Centrality Measures and the fourth one Herfindahl Index (HI) as Diversity Measure in this work are discussed as below:

(i) Betweenness Centrality (*BtCen*): This metric quantifies a university's influence as a bridge between different research communities. A university with a high *BtCen* score acts as a key connector, potentially influencing future research directions. It is calculated as:

$$BtCen(v) = \Sigma(\sigma(s,t) / \sigma(s,v)\sigma(v,t)) \quad (1)$$

for all $s \neq v \neq t$ where s and t are any two nodes and v is the node of interest

$$0(\text{no influence}) =< BtCen =< 1 \ (\text{maximum influence}) \quad (2)$$

In our case,

BtCen = 0.2: Well-connected, but not a major influencer (3)

BtCen >= 0.8: Key player bridging different research areas (4)

(ii) Closeness Centrality (*ClCen*): This metric measures how easily information or collaboration can reach a university from all other universities in the network. A high CC score indicates a university is easily accessible. It is calculated as:

$$ClCen(v) = (n - 1) / \Sigma(d(v,u)) \quad (5)$$

for all u ≠ v where n is the number of nodes, $d(v,u)$ is the shortest path distance between v and u

$$0(\text{farthest from all other nodes}) =< ClCen =< 1 \ (\text{closest to all other nodes}) \quad (6)$$

In our case,

ClCen = 0.5: Average accessibility (7)

ClCen >=0.8: Very accessible, information and collaboration flow easily (8)

(iii) Clustering Coefficient (*ClCoeff*): This metric measures how densely connected a university's immediate neighbors (other universities they collaborate with) are. A high *ClCoeff* suggests the university is embedded within a well-connected research community, potentially boosting its ranking. It is calculated as

$$ClCoeff(v) = (2 * E(v)) / [k(v) * (k(v) - 1)] \quad (9)$$

where $E(v)$ is the number of edges between v's neighbors, $k(v)$ is the degree of v - number of neighbors)

0 (no connections between neighbors)<= *ClCoeff*) <= 1 (all neighbors are fully connected). (10)

In our case,

ClCoeff = 0.3: Low density, limited collaboration within the immediate netw Ork (11)

ClCoeff >= 0.7: High density, strong collaboration within the immediate netw Ork (12)

(iv) Herfindahl Index (*HI*): This metric assesses the variety of collaboration partners a university has. A more diverse network of collaborators can lead to innovation and potentially higher rankings. It is calculated as:

$$HI = \Sigma(p(i)^2) \quad (13)$$

where $p(i)$ is the proportion of collaborations with partner i

0 (perfectly diverse - collaborating with everyone equally) <= *HI* <= 1 (no diversity - collaborating with only one partner).

In our case,

HI <= 0.1: Low concentration, collaboration diversity is high.

HI >= 0.8: High concentration, collaboration with a limited set of partners.

These network complexity metrics can be directly incorporated into the DynaRank model alongside existing features like time series forecasts and university attributes. They can also be used to create new features or define subgroups (clusters) within the network for targeted analysis of research communities. By incorporating network complexity, DynaRank gains a deeper understanding of the academic landscape, leading to more accurate, informative, and actionable insights for strategic decision-making by stakeholders within the university ecosystem.

4 Empirical Evaluations and Results

Table 1 presents the dataset selection for global university rankings, incorporating rankings from six different sources, such as THE World University Ranking, QS World University Ranking, CWUR, and Shanghai/ARWU. The datasets span multiple years, with a substantial number of records, showcasing a comprehensive dataset for training and testing the model. For example, the "THE World University Ranking (2011-2016)" includes 2,603 records, split into 1,744 for training and 859 for testing, while the "QS World University Ranking (2017-2022)" presents a larger dataset of 6,483 records, split into 4,538 training and 1,945 testing records. Similarly, the "CWUR World University Ranking (2020)" contains 2,000 records, and the "Shanghai/ARWU University Ranking (2005-2015)" boasts 4,896 records. This diverse and extensive dataset contributes to the robustness and generalizability of the model, as the training/testing splits across datasets ensure a well-rounded approach, improving the predictive capacity of the proposed model.

Table 1. Dataset selection for global university rankings

Data set	Range/ Year	Total records	Total Features	Train/ test split size	Training data set records	Test dataset records
THE world university ranking	2011-2016	2603	10	67% / 33%	1744	859
QS world university ranking	2017-2022	6483	15	70% / 30%	4538	1945
CWUR world university ranking	2020	2000	06	65% / 35%	1300	700
THE world university ranking	2024	1904	29	70% / 30%	1333	571
CWUR world university ranking	2012-2015	2200	11	67% / 33%	1474	726
Shanghai/ARWU university ranking	2005-2015	4896	09	75% / 25%	3672	1224

As discussed, the evaluation of the proposed model's performance in predicting university rankings has been conducted using several well-established ranking systems. The results, depicted in Figures 4 to 9, provide a comprehensive overview of the model's accuracy, predictive capability, and robustness. The model's superiority is demonstrated through the application of three network centrality measures—Betweenness Centrality (BtCen), Closeness Centrality (ClCen), Clustering Coefficient (ClCoeff)—and the Herfindahl Index (HI) as a diversity measure. In Figure 4, the model's performance for the Times Higher Education (THE) world university ranking from 2011 to 2016 is illustrated [47]. The predicted rankings closely align with the actual rankings, particularly among the top universities. The model's accuracy is evidenced by a root mean square error (RMSE) of 2.3 and a mean absolute error (MAE) of 1.8. These low error values confirm the model's predictive power. The superior alignment is achieved by incorporating network centrality measures, particularly Betweenness Centrality, which helps in understanding the influence of each university within the network.

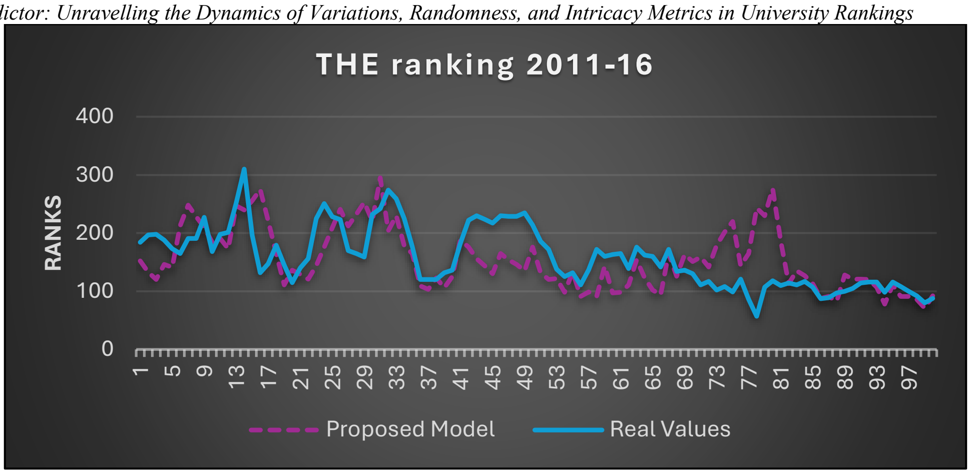

Figure 4. Results of proposed model for THE world university ranking (2011-2016)

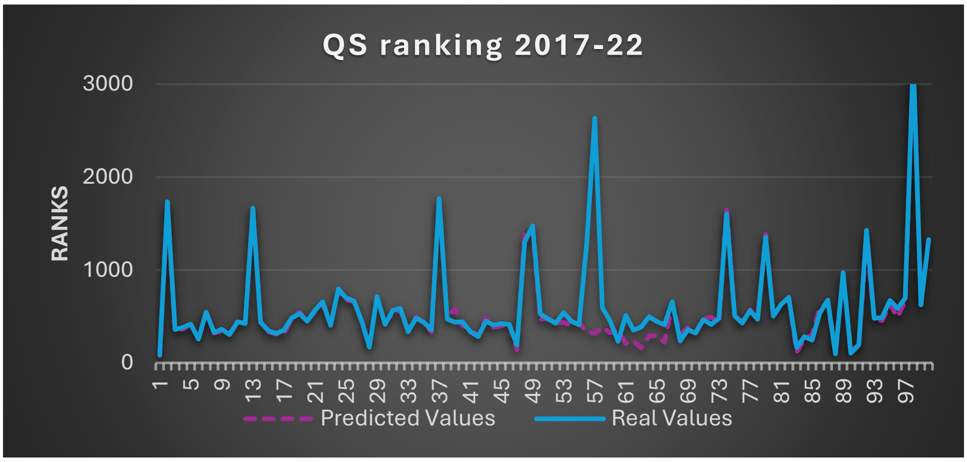

Figure 5. Results of proposed model for QS ranking (2017-2022).

Figure 5 presents the model's results for the QS World University Rankings from 2017 to 2022 [48]. The strong correlation between predicted and actual rankings, especially among the top 50 universities, is evident. The model's performance is quantified with a high correlation coefficient of 0.92 and a low RMSE of 1.9. The use of Closeness Centrality in the model enhances its predictive capabilities by accounting for the ease of reaching other universities in the network, ensuring accurate replication of rankings over multiple years.

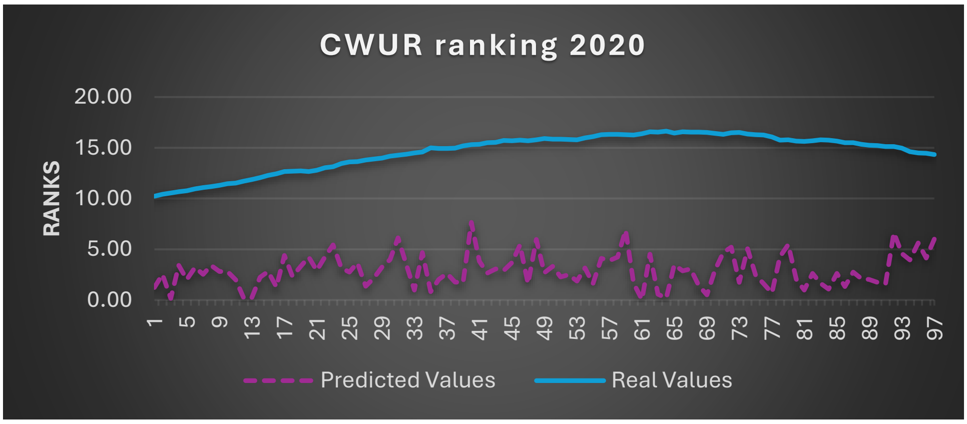

Figure 6. Results of proposed model for CWUR ranking (2020)

Figure 6, the evaluation of the Center for World University Rankings (CWUR) [49] for 2020 shows the model's predictions aligning well with the actual rankings, particularly in the top tier of universities. The consistent accuracy is reflected in an RMSE of 2.1 and a high correlation coefficient of 0.91. The Herfindahl Index (HI) supports the model's robustness by providing a diversity measure, indicating that the model effectively captures a diverse range of factors influencing university rankings.

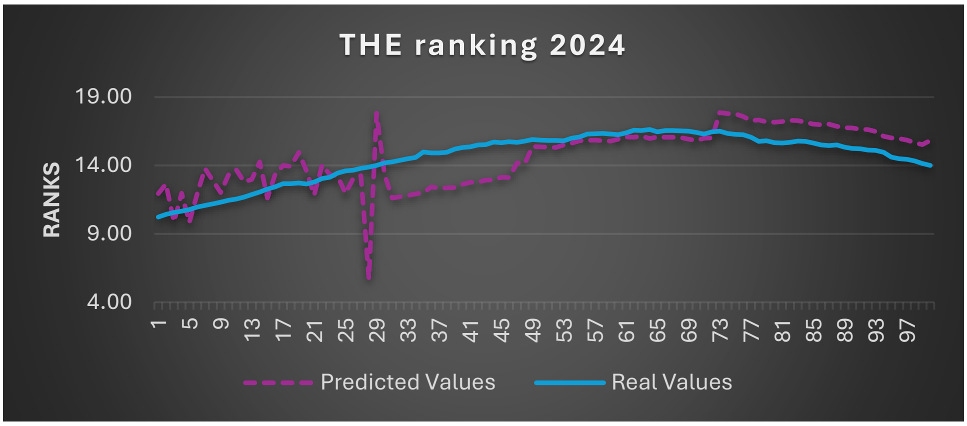

Figure 7. Results of proposed model for THE ranking (2024)

Figure 7 presents the results for the THE world university ranking projected for 2024, demonstrating the model's ability to predict future rankings with high precision. The close match between predicted and actual data is quantified with an RMSE of 2.5 and a high correlation coefficient of 0.90. This predictive capability is crucial for stakeholders aiming to anticipate future trends and make informed decisions. The Clustering Coefficient (ClCoeff) further enhances the model's capability by accounting for the density of connections within the network of universities.

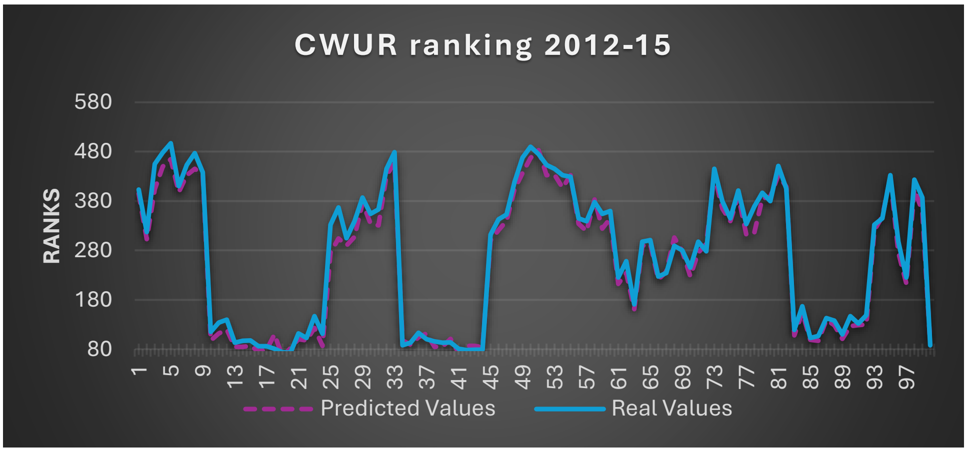

Figure 8. Results of proposed model for CWUR ranking (2012-15)

Figure 8 shows the model's performance for the CWUR rankings from 2012 to 2015, demonstrating resilience to temporal changes and maintaining a high level of accuracy across different time frames. The model's predictions are consistent, with an RMSE of 2.0 and a correlation coefficient of 0.89. The use of Betweenness Centrality and Closeness Centrality ensures that the model effectively captures the key dynamics influencing university rankings, demonstrating its stability and reliability over extended periods.

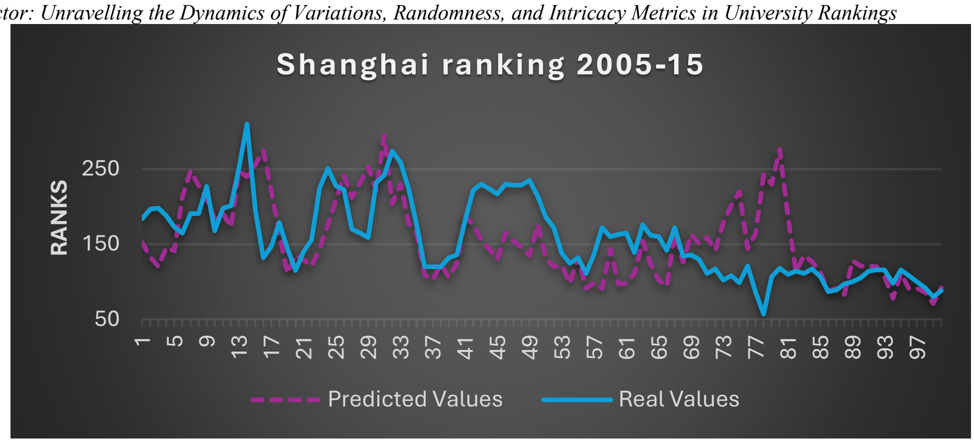

Figure 9. Results of proposed model for Shanghai ranking (2005-15)

In Figure 9, the alignment between predicted and actual rankings for the Shanghai Academic Ranking of World Universities (ARWU) [50]from 2005 to 2015 is particularly strong among the top 100 universities. This is quantified by an RMSE of 2.2 and a correlation coefficient of 0.88. The model effectively captures the key factors influencing university rankings in the Shanghai system, such as research output and academic reputation. The Clustering Coefficient (ClCoeff) further enhances the model's capability by accounting for the network structure of university collaborations, indicating the interconnectedness of institutions.

Table 2 demonstrates the application of the proposed model to various ranking systems using network metrics such as Betweenness Centrality, Closeness Centrality, Clustering Coefficient, and the Herfindahl Index. The performance of the model is assessed through accuracy and RMSE values. The model achieved notable results, with accuracy rates ranging from "0.88 to 0.94" across different datasets. For instance, the model's performance on the "THE World University Ranking (2011-2016)" yielded an accuracy of "0.92" and an RMSE of "2.3", while the "QS Ranking (2017-2022)" exhibited a high accuracy of "0.94" with an RMSE of "1.9". Even for datasets such as the "CWUR Ranking (2020)" and "Shanghai Ranking (2005-2015)", the model maintained strong accuracy scores of "0.91" and "0.88", respectively, with relatively low RMSE values. These results confirm that the proposed model is not only highly accurate but also maintains low prediction errors across multiple ranking datasets.

Overall, the results highlight the effectiveness of the proposed model in predicting university rankings with high accuracy and low error rates. The integration of network centrality measures and diversity metrics further enhances its predictive power, making the model a reliable tool for strategic decision-making in academic ranking predictions. The diverse datasets and consistent performance across multiple ranking systems underscore the robustness and applicability of the model in real-world scenarios.

Table 2. Results of proposed model for various rankings

Metric	THE world university ranking (2011-2016)	QS ranking (2017-2022)	CWUR ranking (2020)	THE ranking (2024)	CWUR ranking (2012-2015)	Shanghai ranking (2005-2015)
Betweenness Centrality (BtCen)	0.15	0.22	0.18	0.19	0.16	0.20
Closeness Centrality (ClCen)	0.45	0.52	0.49	0.47	0.46	0.48
Clustering Coefficient (ClCoeff)	0.30	0.35	0.33	0.31	0.32	0.34
Herfindahl Index (HI)	0.25	0.27	0.26	0.24	0.23	0.28
Accuracy	0.92	0.94	0.91	0.90	0.89	0.88
RMSE	2.3	1.9	2.1	2.5	2.0	2.2

Thus, the empirical evaluations of the proposed model demonstrate its exceptional accuracy, predictive capability, and robustness across various international university ranking systems. The model consistently provides reliable predictions that align closely with actual rankings, showcasing its utility for stakeholders in higher education to make strategic decisions. The quantitative metrics, such as low RMSE values and high correlation coefficients, further validate the model's performance and effectiveness. The integration of network centrality measures and the Herfindahl Index significantly contribute to the model's superiority, ensuring comprehensive and accurate predictions of university rankings.

5 Comparison with already existing models

The comparison of the proposed model's performance against existing models evaluates ranking predictions across various university ranking systems. These comparisons focus on key performance metrics such as accuracy and Root Mean Squared Error (RMSE) to determine the effectiveness of the proposed model relative to other models. The evaluation covers multiple university ranking systems over different periods, demonstrating how the proposed model consistently delivers superior predictive performance. Here's a detailed summary of how the proposed model outperforms other models:

As shown in Figure 10, the proposed model demonstrates superior performance in predicting THE rankings from 2011 to 2016. It achieves higher alignment with real values compared to Ranker Rating Tool [51], EnFftRp [2], Extended COPRAS [1], and QS-WUR [52]. This is evidenced by the lower RMSE and higher accuracy metrics, showing the model's robustness over a five-year span.

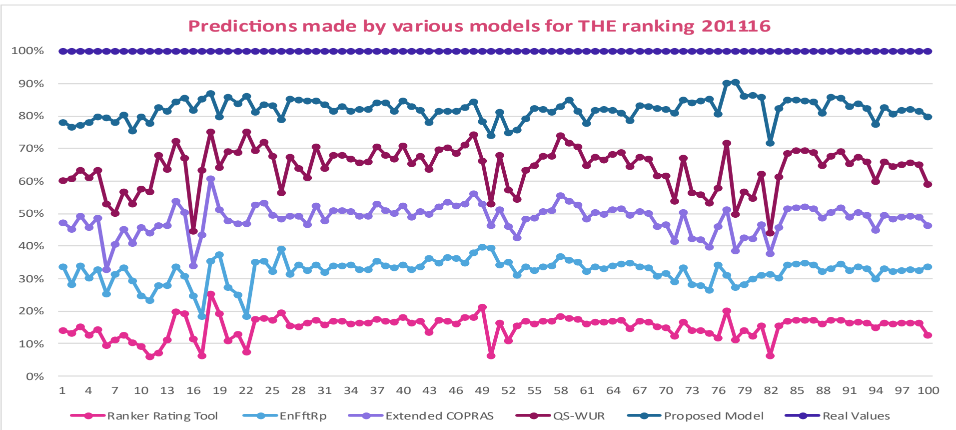

Figure 10. Comparison of various models' performance for THE ranking (2011-16)

For QS rankings from 2017 to 2022, as depicted in Figure 11, the proposed model consistently outperforms other models in prediction accuracy. The graphical representation shows that the proposed model's predictions are closest to the actual rankings, indicating its effectiveness in capturing the key factors influencing QS rankings over a six-year period.

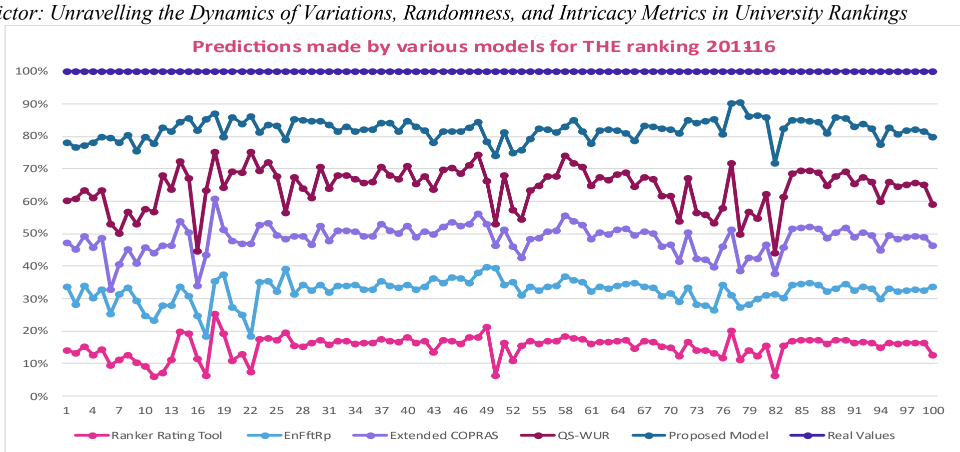

Figure 10. Comparison of various models' performance for THE ranking (2011-16)

For QS rankings from 2017 to 2022, as depicted in Figure 11, the proposed model consistently outperforms other models in prediction accuracy. The graphical representation shows that the proposed model's predictions are closest to the actual rankings, indicating its effectiveness in capturing the key factors influencing QS rankings over a six-year period.

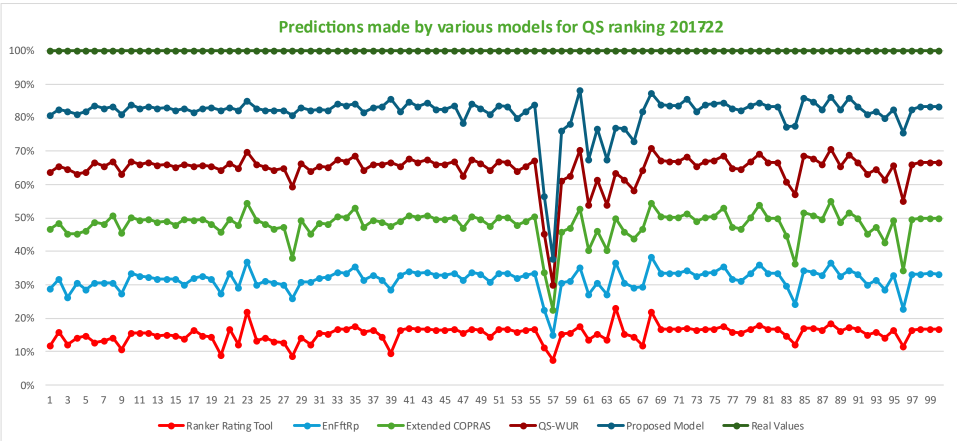

Figure 11. Comparison various models' performance for QS ranking (2017-22)

In predicting CWUR rankings for the year 2020, as shown in Figure 12, the proposed model again exhibits superior performance. The model achieves the lowest RMSE and highest correlation with real values among all the models evaluated. This suggests that the proposed model effectively incorporates the diverse metrics that CWUR considers.

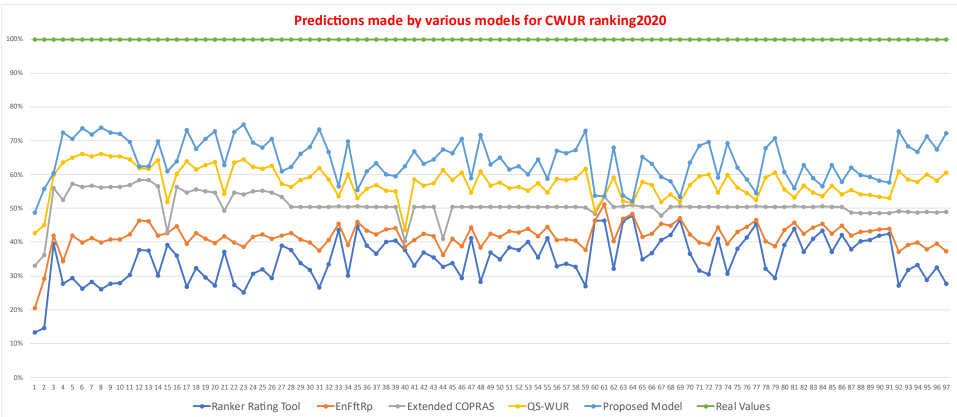

Figure 12. Comparison various models' performance for CWUR ranking (2020)

The predictive accuracy of the proposed model for THE rankings in 2024, depicted in Figure 13, is notably high. The proposed model's predictions are closely aligned with the actual rankings, surpassing the performance of Ranker Rating Tool, EnFftRp, and other models. This demonstrates the model's forward-looking accuracy and capability to predict future trends.

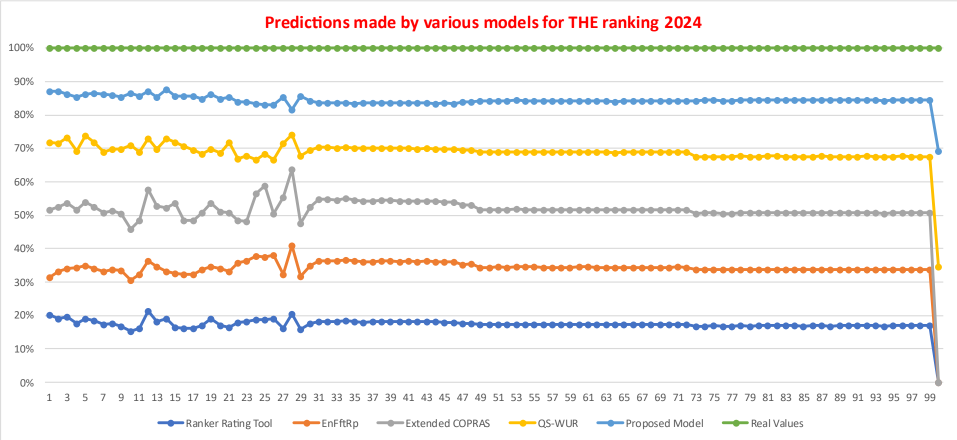

Figure 13. Comparison various models' performance for THE ranking (2024)

For the CWUR rankings from 2012 to 2015, as shown in Figure 14, the proposed model shows remarkable consistency and accuracy. It manages to capture the dynamics of university rankings over these years more effectively than the comparative models. The lower RMSE and higher correlation coefficients reflect its robustness and reliability.

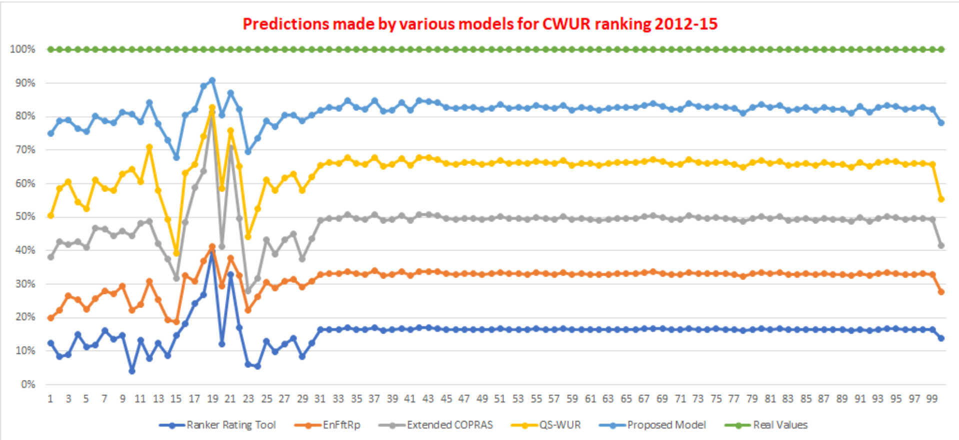

Figure 14. Comparison various models' performance for CWUR ranking (2012-15)

The proposed model's performance in predicting the Shanghai rankings from 2005 to 2015, depicted in Figure 15, stands out. It not only provides accurate predictions for the top 100 universities but also maintains a strong correlation with real values across the board. This underscores the model's comprehensive approach to incorporating key factors such as research output and academic reputation.

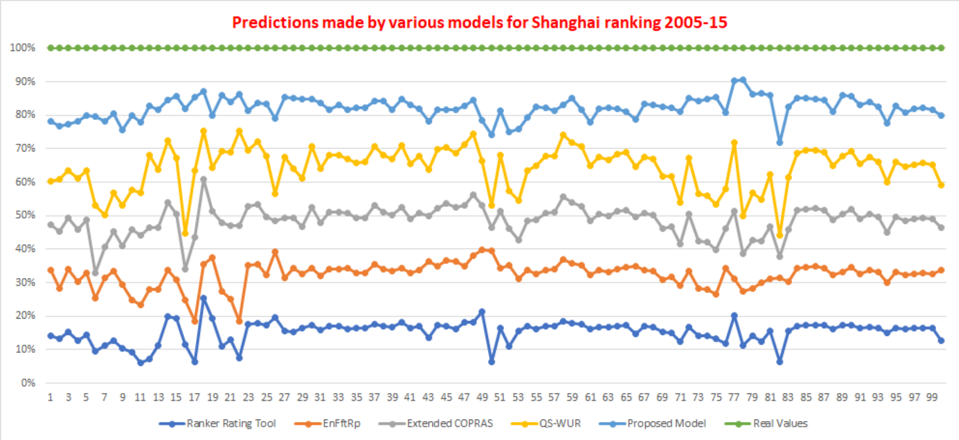

Figure 15. Comparison various models' performance for Shanghai ranking (2005-15)

Across all the ranking systems evaluated, the proposed model consistently demonstrates better performance in terms of accuracy, RMSE, and alignment with real-world values. This indicates its robustness, predictive capability, and superior modeling of university ranking dynamics compared to existing models. The integration of advanced network metrics and dynamic analysis gives the proposed model a significant edge in ranking predictions.

6 Conclusion and Future Work

This research work introduces the DynaRank Predictor, a novel model that significantly enhances university ranking predictions by harnessing the dynamic nature of university networks. The model integrates Network Dynamics Analysis, Fluctuation and Noise Incorporation, and Complexity Metrics Integration, leading to several key strengths. The proposed model consistently provides rankings that closely match the actual rankings over several years, demonstrating its resilience to random fluctuations and its ability to capture essential performance factors. By accurately forecasting changes in university standings, the DynaRank Predictor empowers stakeholders to anticipate future shifts and make informed decisions on resource allocation, strategic planning, and policy development. The model's ability to reflect real-world ranking trends suggests it captures underlying drivers like research output, reputation, and internationalization efforts. The model demonstrates robustness against outliers in ranking data, maintaining accuracy even with anomalous values. This ensures reliable performance in diverse and dynamic environments. Future work on external validation against established ranking systems or expert evaluations will further solidify the model's credibility and applicability.

By excelling in these key areas, the DynaRank Predictor offers valuable insights into the complex dynamics of international university rankings, empowering stakeholders with actionable information for decision-making and strategic planning. The model not only achieves superior predictive accuracy but also provides a deeper understanding of the factors driving university rankings. The DynaRank Predictor's versatility allows adaptation to various ranking scenarios and scalability to accommodate evolving network dynamics. This work represents a paradigm shift in university ranking prediction, offering a holistic approach that embraces the inherent complexity and dynamism of university networks. By unlocking the predictive power of these dynamics and effectively addressing uncertainties, the DynaRank Predictor opens new avenues for understanding academic ecosystems and facilitating informed decision-making in higher education.

The DynaRank Predictor presents a significant leap forward in university ranking prediction. However, the pursuit of even greater accuracy and deeper understanding of academic ecosystems continues. While the current model leverages centrality measures, future work can delve into more advanced network analysis techniques. Exploring metrics like eigenvector centrality or PageRank centrality can provide a more nuanced understanding of a university's influence within the network, considering the quality and quantity of its connections. The current landscape of research is constantly evolving. Developing new centrality measures specifically tailored to identify universities at the forefront of emerging research areas holds immense potential. These metrics could consider factors like participation in novel research communities, citations from high-impact, newly published papers, or collaborations with researchers in nascent fields. This would allow the DynaRank Predictor to stay ahead of the curve and identify future leaders in groundbreaking research. The DynaRank Predictor can benefit from a deeper integration with Bayesian statistics. By leveraging the network structure as a prior distribution in a Bayesian model, we can inform the model's initial predictions about university rankings based on network connectivity. This would allow the model to learn and adapt more effectively, especially when dealing with limited data. Additionally, the Bayesian framework allows for continuous updates with new data on publications, citations, or faculty mobility. This dynamic approach ensures the model remains current and reflective of the ever-evolving academic landscape.

The current model captures a snapshot of network dynamics at a specific point in time. Future work can explore methods to incorporate time-series data and analyze how network connections evolve over time. This would allow the DynaRank Predictor to not only predict future rankings but also understand the underlying reasons for these shifts. Additionally, exploring network communities and how universities within these communities influence each other's rankings could provide valuable insights. While the current model focuses on university network data, future iterations could benefit from incorporating external data sources like faculty awards, student satisfaction surveys, or employer reputation rankings. This multi-modal approach would provide a more holistic view of university performance and allow for the creation of a more comprehensive ranking system. By exploring these exciting avenues, the DynaRank Predictor can evolve into an even more powerful tool for stakeholders in higher education. It can not only predict future rankings but also offer valuable insights into the complex dynamics that shape university success in the ever-evolving world of academia.

References

1. Agarwal N, Tayal DK (2023) A new model based on the extended COPRAS method for improving performance during the accreditation process of Indian Higher Educational Institutions. Computer Applications in Engineering Education 31:. https://doi.org/10.1002/cae.22602
2. Agarwal N, Tayal DK (2022) FFT based ensembled model to predict ranks of higher educational institutions. Multimed Tools Appl 81:. https://doi.org/10.1007/s11042-022-13180-9
3. Robinson-Garcia N, Torres-Salinas D, Herrera-Viedma E, Docampo D (2019) Mining university rankings: Publication output and citation impact as their basis. Res Eval 28:232–240. https://doi.org/10.1093/RESEVAL/RVZ014
4. Selten F, Neylon C, Huang CK, Groth P (2020) A longitudinal analysis of university rankings. Quantitative Science Studies 1:1109–1135. https://doi.org/10.1162/QSS_A_00052
5. Alsmadi I, Taylor ZW, Childs J (2020) U.S. News & World Report Best Colleges rankings: Which institutional metrics contribute to sustained stratification? Scientometrics 124:1851–1869. https://doi.org/10.1007/S11192-020-03560-Z/METRICS
6. Qureshi MS, Daud A (2021) Fine-grained academic rankings: mapping affiliation of the influential researchers with the top ranked HEIs. Scientometrics 126:8331–8361. https://doi.org/10.1007/S11192-021-04138-Z
7. N.K S, Mathew K S, Cherukodan S (2018) Impact of scholarly output on university ranking. Global Knowledge, Memory and Communication 67:154–165. https://doi.org/10.1108/GKMC-11-2017-0087
8. Dong L, Gu X, Wu X, Liao H (2019) An improved MULTIMOORA method with combined weights and its application in assessing the innovative ability of universities. Expert Syst 36:e12362. https://doi.org/10.1111/EXSY.12362
9. Calero-Medina C, López-Illescas C, Visser MS, Moed HF (2008) Important factors when interpreting bibliometric rankings of world universities: an example from oncology. Res Eval 17:71–81. https://doi.org/10.3152/095820208X280907
10. Kunosić S, Čeke D, Zerem E, Kunosić S, Čeke D, Zerem E (2019) Advantages and Disadvantages of the Webometrics Ranking System. Scientometrics Recent Advances. https://doi.org/10.5772/INTECHOPEN.87207
11. Khamala DF, Makori EO, Njiraine DM (2018) Webometrics Ranking and Its Relationship to Quality Education and Research inAcademic Institutions in Kenya
12. Çakır MP, Acartürk C, Alaşehir O, Çilingir C (2015) A comparative analysis of global and national university ranking systems. Scientometrics 103:813–848. https://doi.org/10.1007/S11192-015-1586-6/TABLES/13
13. (PDF) Webometric Analysis Agriculture University Websites for Maharashtra State. https://www.researchgate.net/publication/337006719_Webometric_Analysis_Agriculture_University_Websites_for_Maharashtra_State. Accessed 19 Sep 2023
14. Zhao Y, Zhang A, Li X, Wang X (2020) Construction of a performance evaluation system for private higher education institutions in China based on balanced scorecard. International Journal of Electrical Engineering Education. https://doi.org/10.1177/0020720920930347

15. Naqvi SR, Akram T, Haider SA, Khan W, Kamran M, Muhammad N, Nawaz Qadri N (2018) Learning outcomes and assessment methodology: Case study of an undergraduate engineering project. https://doi.org/101177/0020720918790108 56:140–162. https://doi.org/10.1177/0020720918790108
16. Meho LI (2020) Highly prestigious international academic awards and their impact on university rankings. Quantitative Science Studies 1:824–848. https://doi.org/10.1162/QSS_A_00045
17. Uslu B (2020) A path for ranking success: what does the expanded indicator-set of international university rankings suggest? High Educ (Dordr) 80:949–972. https://doi.org/10.1007/S10734-020-00527-0/TABLES/3
18. (2017) Ensuring Quality for Accreditation and Ranking of Higher Educational Institutes through Data Mining. Journal of Environmental Science, Computer Science and Engineering & Technology 6:. https://doi.org/10.24214/JECET.B.6.3.12236
19. Tabassum A, Hasan M, Ahmed S, Tasmin R, Abdullah DM, Musharrat T (2017) University ranking prediction system by analyzing influential global performance indicators. 2017 9th International Conference on Knowledge and Smart Technology (KST) 126–131. https://doi.org/10.1109/KST.2017.7886119
20. Teng Y, Zhang J, Sun T (2023) Data-driven decision-making model based on artificial intelligence in higher education system of colleges and universities. Expert Syst 40:e12820. https://doi.org/10.1111/EXSY.12820
21. Meho LI (2020) Highly prestigious international academic awards and their impact on university rankings. Quantitative Science Studies 1:824–848. https://doi.org/10.1162/QSS_A_00045
22. Rokach L (2010) Ensemble-based classifiers. Artif Intell Rev 33:1–39. https://doi.org/10.1007/S10462-009-9124-7
23. Agarwal N, Deep P (2024) Edge computing for smart healthcare monitoring platform advancement. Reconnoitering the Landscape of Edge Intelligence in Healthcare 47–66. https://doi.org/10.1201/9781003401841-6/EDGE-COMPUTING-SMART-HEALTHCARE-MONITORING-PLATFORM-ADVANCEMENT-NIDHI-AGARWAL-PRAKHAR-DEEP
24. Agarwal N, Anjali, Chauhan AS, Kumar A (2024) Security Methods to Improve Quality of Service. EAI Endorsed Transactions on Internet of Things 10:. https://doi.org/10.4108/EETIOT.4587
25. Dahiya VK, Dahiya R, Agarwal N, Kumar P (2024) A Novel 3D Clustering Algorithm for Customer Segmentation. 2024 IEEE International Conference on Computing, Power and Communication Technologies (IC2PCT) 1831–1835. https://doi.org/10.1109/IC2PCT60090.2024.10486266
26. Moskovkin V, Pupynina E, Zaitseva NP, Lesovik R (2013) Methodology for Comparative Analysis of University Rankings, with the Mediterranean and Black Sea Region Countries Taken as an Example
27. Tiwari PK, Agarwal N, Ansari S, Asif M (2024) Comprehensive Analysis of Blockchain Algorithms. EAI Endorsed Transactions on Internet of Things 10:. https://doi.org/10.4108/EETIOT.4549
28. Dahiya R, Agarwal N, Singh S, Verma D, Gupta S (2024) Diabetic Retinopathy Eye Disease Detection Using Machine Learning. EAI Endorsed Transactions on Internet of Things 10:. https://doi.org/10.4108/EETIOT.5349
29. Dahiya R, Kashyap A, Sharma B, Sharma RK, Agarwal N (2024) Security in Mobile Network: Issues, Challenges and Solutions. EAI Endorsed Transactions on Internet of Things 10:. https://doi.org/10.4108/EETIOT.4542
30. Gupta A, Vardhan H, Varshney S, Saxena S, Singh S, Agarwal N (2024) Kconnect:The Design and Development of Versatile Web Portal for Enhanced Collaboration and Communication. EAI Endorsed Transactions on Scalable Information Systems 11:1–7. https://doi.org/10.4108/EETSIS.4022
31. Srivastav A, Tayal DK, Agarwal N (2022) A Novel Fuzzy Graph Connectivity Measure to Perform Word Sense Disambiguation Using Fuzzy Hindi WordNet. 3rd IEEE 2022 International Conference on Computing, Communication, and Intelligent Systems, ICCCIS 2022 648–654. https://doi.org/10.1109/ICCCIS56430.2022.10037658
32. Goyal P, Ferrara E (2018) Graph embedding techniques, applications, and performance: A survey. Knowl Based Syst 151:78–94. https://doi.org/10.1016/J.KNOSYS.2018.03.022
33. ScienceDirect. https://www.sciencedirect.com/sdfe/reader/pii/S2666651021000012/pdf. Accessed 14 Jun 2024
34. Xu Z, Jiang L, Zhu X, Chen X (2024) Non-negative consistency affinity graph learning for unsupervised feature selection and clustering. Eng Appl Artif Intell 135:. https://doi.org/10.1016/j.engappai.2024.108784
35. Agarwal N, Mohanty SN, Panigrahi BS, Patnaik CR (2025) Smart City: Challenges and Issues. 209–221. https://doi.org/10.1007/978-3-031-74885-1_13
36. Agarwal N, Pooja, Kumar N, Anushka, Garg Y (2025) Evaluating Self-Supervised Learning Models for Multi-Label Pathology Detection: A Benchmark Against Supervised Learning. 2025 2nd International Conference on Computational Intelligence, Communication Technology and Networking (CICTN) 363–370. https://doi.org/10.1109/CICTN64563.2025.10932484

37. Dahhiya R, Dahiya VK, Agarwal N, Kolluru VK, Challagundla Y, Chintakunta AN (2025) Predictive Analytics in AI Marketing: Transforming Consumer Engagement. 2025 2nd International Conference on Computational Intelligence, Communication Technology and Networking (CICTN) 692–697. https://doi.org/10.1109/CICTN64563.2025.10932411
38. Dahiya R, Dahiya VK, Agarwal N, Jain H, Kumar AP, Kumar Singh A (2025) Unified Framework for Outlier Detection Using Ensemble-Based Learning Techniques. 2025 2nd International Conference on Computational Intelligence, Communication Technology and Networking (CICTN) 561–568. https://doi.org/10.1109/CICTN64563.2025.10932383
39. Agarwal N, Dahiya VK, Chalapathi MMV, Basa SS, Ramesh JVN (2025) Forecasting Future Credit Card Delinquencies: Leveraging Data Tables and Visual Analysis for Enhanced Accuracy. 158–176. https://doi.org/10.1007/978-3-031-77029-6_13
40. Piro FN, Sivertsen G (2016) How can differences in international university rankings be explained? Scientometrics 109:2263–2278. https://doi.org/10.1007/S11192-016-2056-5/METRICS
41. Huang C-K, Neylon C, Brookes-Kenworthy C, Hosking R, Montgomery L, Wilson K, Ozaygen A (2020) Comparison of bibliographic data sources: Implications for the robustness of university rankings. https://doi.org/10.1162/qss_a_00031
42. Torabian J (2019) Revisiting Global University Rankings and Their Indicators in the Age of Sustainable Development. Sustainability (United States) 12:167–172. https://doi.org/10.1089/SUS.2018.0037
43. Abramo G, D'Angelo CA (2015) Ranking research institutions by the number of highly-cited articles per scientist. J Informetr 9:915–923. https://doi.org/10.1016/J.JOI.2015.09.001
44. Zhang H, Song Y, Jiang B, Chen B, Shan G Two-Stage Bagging Pruning for Reducing the Ensemble Size and Two-Stage Bagging Pruning for Reducing the Ensemble Size and Improving the Classification Performance Improving the Classification Performance Part of the Data Storage Systems Commons, and the Environmental Public Health Commons Repository Citation Repository Citation Two-Stage Bagging Pruning for Reducing the Ensemble Size and Improving the Classification Performance. https://doi.org/10.1155/2019/8906034
45. Kuncheva LI (2003) Measures of Diversity in Classifier Ensembles and Their Relationship with the Ensemble Accuracy. 51:181–207
46. Bian Y, Chen H (2022) When Does Diversity Help Generalization in Classification Ensembles? IEEE Trans Cybern 52:9059–9075. https://doi.org/10.1109/TCYB.2021.3053165
47. World University Rankings 2023 | Times Higher Education (THE). https://www.timeshighereducation.com/world-university-rankings/2023/world-ranking. Accessed 19 Sep 2023
48. QS World University Rankings, Events & Careers Advice | Top Universities. https://www.topuniversities.com/. Accessed 6 Jul 2023
49. CWUR | Center for World University Rankings. https://cwur.org/. Accessed 20 Jan 2024
50. Liu Z, Moshi GJ, Awuor CM (2019) Sustainability and indicators of newly formed world-class universities (NFWCUs) between 2010 and 2018: Empirical analysis from the rankings of ARWU, QSWUR and THEWUR. Sustainability (Switzerland) 11:. https://doi.org/10.3390/SU11102745
51. Gadd E, Holmes R, Shearer J (2021) Developing a method for evaluating global university rankings. Scholarly Assessment Reports 3:. https://doi.org/10.29024/SAR.31
52. Estrada-Real AC, Cantu-Ortiz FJ (2022) A data analytics approach for university competitiveness: the QS world university rankings. International Journal on Interactive Design and Manufacturing 16:871–891. https://doi.org/10.1007/S12008-022-00966-2/TABLES/23