Data-Driven Analysis of Student Enrollment Trends Using Machine Learning Algorithms: A Case Study of the University of Tetova

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Abstract: - More than just numbers, data tools now help un-cover how students move through universities. From 2021 to 2024, patterns in who enrolls where at the University of Tetova were mapped using code, not guesswork. Python cleaned the records first; then came visual scans, grouping similar cases, and mapping choices like branches on a tree. Medical Sciences stands out, drawing more interest year after year than other faculties. Instead of relying on assumptions, predictions grow from what past behavior suggests might happen next. These models do not replace judgment; they sharpen it with evidence most overlook. What began in technology labs now finds purpose inside academic halls, shifting how leaders respond to change. Not limited to stores or factories, smart number crunching proves useful wherever decisions matter. Behind every trend line is a story about people, shaped quietly by mathematics working behind the scenes.

Key-Words: - data science; machine learning; higher edu-cation analytics; computational methods; student enrollment; educational data mining; K-Means clustering; decision tree classification; linear regression forecasting; university analytics

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1 Introduction

These days, colleges across the globe are leaning more on numbers to shape their choices and run things more smoothly. Thanks to the flood of digital information, from class signups and virtual classrooms to office logs, schools can now base decisions on real patterns. Looking closely at who enrolls where has become a key focus, guiding how campuses prepare ahead, assign teachers, and map out future programs. Figuring out why learners pick certain departments shows more than

just which fields draw crowds; it hints at job shifts, social norms, and even wider habits shaping up behind the scenes.

Using computers to study enrollment numbers has changed how we see the data. Instead of just averages and totals, new tools dig deeper. Methods like exploratory data analysis uncover what is really happening beneath the surface. Hidden groups appear when schools are sorted by similar traits, which is what K-Means does. These groupings show which departments grow, stay flat, or shrink over time. Patterns emerge without being obvious at first glance. One model might split results using clear if-then steps based on choices students make. Trees help explain why some areas attract more people than others. Predictions about next year's numbers come from tracking past movement across years. Numbers shift slowly; watching them closely makes changes easier to spot ahead of time.

All around the world, research into how data shapes educa-tion has shown real benefits for school administrators making choices. Not just in theory: colleges across North America and parts of Europe now apply algorithms to keep students enrolled, anticipate which classes will fill up, and distribute staff and budgets more efficiently. Places with fewer resources have used similar tools to uncover what keeps children out of classrooms, opening doors to fairer rules based on actual patterns. Over time, depending more on number-crunching methods has not just caught on; it reveals how fields like teaching strategy, computing, and public policy can actually fit together.

One of the main universities in North Macedonia, the University of Tetova, offers a solid example for this kind of look. Housed within it are many faculties, each shaped by distinct scholarly roots and guiding students toward varied professional routes. In recent years, the Faculty of Medical Sciences has grown more quickly than others, becoming the top choice among applicants, driven partly by regional need for doctors and nurses, and partly by worldwide shifts in study interests. Meanwhile, several other departments see steady numbers or fewer newcomers, hinting at mismatches between what learners want, what schools can offer, and where jobs actually exist. One thing stands out right away: enrollment numbers at the University of Tetova between 2021 and 2024 reveal clear shifts when broken down by faculty and gender. Instead of just summarizing trends, the study digs deeper using clustering, which uncovers hidden patterns others might miss. Classification steps in next, sorting students into meaningful groups based on academic paths, while regression helps forecast future flows. These tools together do more than describe what happened; they hint at what could come. Behind the scenes, decisions in universities often rely on gut feeling, yet here data takes center stage.

When algorithms shape understanding, leaders gain leverage before problems arise. Far from being just another technology experiment, this effort ties computation directly to real choices shaping schools. While similar studies exist elsewhere, few focus on the Western Balkans, making this one stand apart. Machine learning is not treated like magic; instead, it is grounded in actual records and measurable outcomes. The whole approach feeds into broader efforts that mine student data thoughtfully. What emerges is not flashiness but quiet power: information used wisely changes direction slowly and steadily. Not every finding demands attention, yet each adds weight to smarter planning.

2 Related Work

Lately, more attention has gone toward digging into school-related numbers using smart software methods. Number-crunching techniques help schools spot patterns in how learn-ers act [1]. These techniques show ways in which such details can point to who might struggle and how classrooms could adjust. More records exist now than ever thanks to online learning systems storing every click and move. That flood of facts means stronger computer-based tools are needed just to make sense of it all. Related work has also focused on helping colleges choose better based on evidence [2]. That work points out that forecasts built from past habits do matter when keeping students enrolled longer, and that schools run more smoothly when guesses about dropout risks come early enough to react. Core ideas about teaching machines to learn without being told each step were laid down years earlier [3]. These concepts quietly power much of what analysts rely on today behind the scenes. Full routes through messy datasets common across academic studies have also been mapped [4].

The methods described there often show up again in papers aiming to uncover hidden classroom truths.

Looking closer at who signs up for courses, other work shows that grouping techniques help spot trends across differ-ent school departments [5]. These groupings pull out invisible clusters in student numbers without needing labels ahead of time. At the same time, labeled predictions build clear guidelines to guess what choices learners might make. Another angle looks at why students stay enrolled, using smart number-crunching tools that adapt well to college planning tasks [6]. What stands out is how many sides there are to signing up: grades matter, so do friendships, plus how schools run their programs. Each layer tugs at whether a student continues or leaves. A separate study took a close look at how clustering methods work in education research, showing clear patterns when sorting learners by habits and grades [7]. Elsewhere, it was found that just knowing who signed up could already hint at who might succeed, proving that basic school records carry more weight than expected [8].

Closer to local realities, one study traces how the University of Tetova took shape historically and institutionally, showing its part in opening doors to higher learning for Albanian speakers in northern Macedonia [9]. Because of this, we get a clearer picture of the structures behind shifts in who enrolls there. Other research digs into what keeps schools running smoothly, such as leadership styles, workplace atmosphere, and decision-making setups, and how these affect how students feel about being involved [10]. When leaders make choices at the organization-wide level, those choices ripple out quietly but clearly into whether learners stay active or sign up. A wider, region-level report lays out deep-rooted problems with money, entry routes, and modernization efforts across colleges in the Western Balkan region [11]; this sets the stage for why numbers go up or down at places like Tetova.

Lately, work has turned toward using smart algorithms to study college outcomes. Not long ago, three techniques (SVM, Random Forest, and CNN) were tested to guess how students move through Indian universities, and the CNN pulled ahead by getting things right most often [12]. What stands out is a quiet trend: older number-crunching tools are being swapped out for deeper, layered models in classrooms. In another case, scholars in China leaned on Random Forest after gathering logs of student actions and sign-up patterns, managing sharp forecasts about who would do well [13]. Even though such group-style methods demand heavy computing power, they handle messy real-life data without falling apart easily. Looking at Europe, student choices in Italy were ex-amined through gradient boosting [14], revealing patterns tied to gender and prior studies shaping paths toward technology-focused subjects. This adds pieces to how societal layers guide who enters technical areas in wealthier nations. Another angle used classification tools to forecast grades in various courses, and showed these techniques hold up well across different learning environments [15]. Moving to engineering learners, it has been pointed out that decision trees bring both clarity and strong results [16]; that insight fits closely with what shapes

the approach here. On a wider scale, a review of algorithms aimed at spotting students likely to leave school stressed that mixed and layered models tend to do better than standalone ones when guessing who might drop out [17].

When it comes to technology setups, handling school-related data well depends on smart system designs and fast search methods. Research has looked into how online services work together, showing that smarter queries speed up access to information across linked systems [18]. A follow-up study proposed using UML diagrams to shape web tools, giving a clear path to map out how data moves through complicated networks [19]. What was built there matters most when dealing with education databases, where large volumes of student sign-up details need quick storage, lookup, and sorting for instant forecasting tasks.

Taken together, this body of work shows how atten-tion worldwide has slowly turned toward forecasting tools and smart algorithms for studying enrollment patterns. Each area focuses on its own set of influences: early research laid groundwork while classic numerical methods followed. Though older methods still exist, experts have increasingly noted how powerful combined models can be; instead of rely-ing on one technique, stacking several together boosts results in surprising ways. Working with big, messy, layered data is something deep learning handles well, including school-related data collections. Earlier research laid the groundwork that this project combines with computational methods such as K-Means clustering and decision trees. Breaking down the data lets us see faculty numbers in finer detail and observe ways things are changing over time. Earlier work looked mostly at basic numbers, whereas this task uses machine learning instead of surveys to sort faculties into groups. Future patterns come into view when we watch how interests shift; watching changes helps spot what comes next in sign-ups, with clues appearing through movement over time, built around how things work at the University of Tetova.

3 Methodology

One way to look at student numbers begins with gathering information, then cleaning it up before digging into patterns. After that comes grouping similar cases, sorting them further, and predicting what might happen next. Tools like Pandas and NumPy help handle the data while Matplotlib draws visuals along the way. Scikit-learn steps in when decisions need to be made based on past examples. All of this runs through code written in Python, shaping each stage from start to finish.

3.1 Data Collection

From 2021 to 2024, student numbers were pulled directly from MAKStat [20], North Macedonia's primary source for education statistics. Every faculty at the University of Tetova is included there, broken down by field of study, gender, and year of enrollment.

3.2 Data Preprocessing

Out of the raw data came a cleaner version; messy elements such as empty columns were removed. Total yearly enroll-ments were then derived through fresh calculations, alongside breakdowns by gender. The data was then shaped into rows and blocks, organized appropriately for machine analysis.

3.3 Exploratory Data Analysis (EDA)

Looking at the data began with simple plots, such as bars, lines, and circles, to spot shifts across time.

Faculty choices started making sense once the shapes revealed who drew more students. Differences between women and men showed up clearly when colors separated the numbers. Each graph acted like a flashlight on one piece of the bigger picture. Year after year, movement either climbed, dipped, or held steady.

3.4 Clustering Using K-Means Algorithm

Outlier patterns showed up when grouping faculties by en-rollment shape; Medical Sciences stood apart clearly. Group-ing was done using K-Means, a method that finds structure without prior labels. Distinct sets emerged naturally, thanks to shared trend behavior across departments.

3.5 Classification Using Decision Tree Algorithm

A pattern began to emerge when each faculty's enrollment shifts were sorted by a Decision Tree into rising, steady, or falling groups. Year-over-year changes in student numbers shaped the learning process behind it. What pushed one group apart from another became clearer through the visible logic paths drawn by the system.

3.6 Forecasting Using Linear Regression

One way to estimate how many students might join the Faculty of Medical Sciences is by using a basic linear model. This method looked at past numbers to project what could happen from 2025 through 2029. Instead of guessing blindly, it followed historical figures to point toward likely totals, with earlier years helping shape each step forward.

Putting these approaches into perspective, Table 1 shows how familiar machine learning techniques stack up when used on enrollment data. Each method reveals its own advantages alongside typical drawbacks, revealing which scenarios suit them most, as well as where they tend to fall short.

Table 1. Comparison of Machine Learning Algorithms for Enrollment Data Analysis

Algorithm	Type	Characteristics (Advantages / Limitations)
K-Means	Unsupervised	Simple and efficient for clustering trends; good at finding groups in data. Sen-sitive to number of clusters and struggles with complex distributions.
Decision Tree	Supervised	Easy to interpret and visual- ize; provides clear decision rules. Prone to overfitting and may have limited gen-eralization.
Linear Regression	Regression	Simple, interpretable, works well for linear patterns. Cannot capture nonlinear relationships; limited accu-racy in complex data.
Random Forest	Supervised	Robust, handles nonlinear- ity and noise well. Requires more computation and re-sults are less interpretable.
SVM	Supervised	Effective in high- dimensional spaces; strong classification ability. Requires parameter tuning and is less interpretable.

Source: created by the authors.

K-Means works well at clustering departments by how many students sign up, yet it does not deliver prediction on its own. Decision Trees give clear categories, such as rising, flat, or falling trends, and their logic flows easily, even if they occasionally learn too much from noise. When lines go steadily upward or downward, Linear Regression provides clean estimates for next year's numbers; however, non-linear twists and turns trip it up. Moving beyond these basics, methods such as Random Forest and SVM capture curved or jagged shifts better, boosting forecasts while requiring heavier computation and more careful setup.

4 Results and Discussion

Looking closer at who signed up showed clear trends regarding what students preferred, along with which faculties drew larger numbers at the University of Tetova between 2021 and 2024.

Source: created by the authors.

4.1 Enrollment Trends Across Faculties

Looking at Figure 1, enrollment totals for every faculty are displayed over the research timeframe. No unit outpaced Medical Sciences in drawing learners; its lead remained firm throughout. That steady flow points to the lasting appeal of medicine as an academic path.

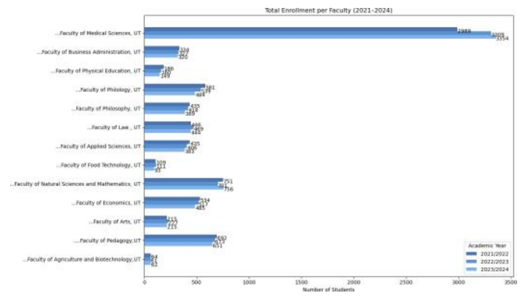

Fig. 1: Total student enrollments by faculty and year

Source: created by the authors, based on MAKStat data [20].

4.2 Gender Distribution

Looking at Figure 2, we see more women than men studying in the Faculty of Medical Sciences. Around the world, the pattern is similar, with more women joining medicine programs. While numbers shift elsewhere too, the trend is clear here.

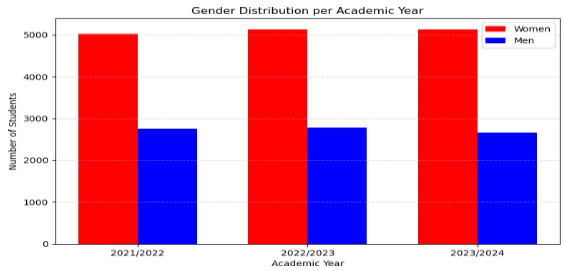

Fig. 2: Gender distribution over the years

Source: created by the authors, based on MAKStat data [20].

4.3 Faculty Clustering Results

Clear patterns emerged when K-Means sorted faculties by student numbers. In Figure 3, one group stands out: Medical Sciences, because it consistently pulls in more students than the others. That steady flow set it apart from the rest.

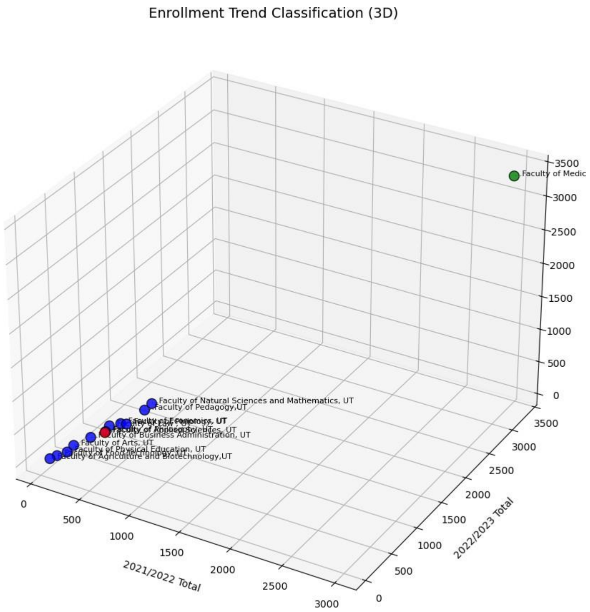

Fig. 3: K-Means clustering of faculties based on enrollment trends

Source: created by the authors.

4.4 Trend Classification Using Decision Tree

One way to sort the faculties used a Decision Tree, placing each into rising, steady, or falling groups based on student numbers. Figure 4 shows Medical Sciences among those gaining more students, suggesting that more applicants are choosing this field.

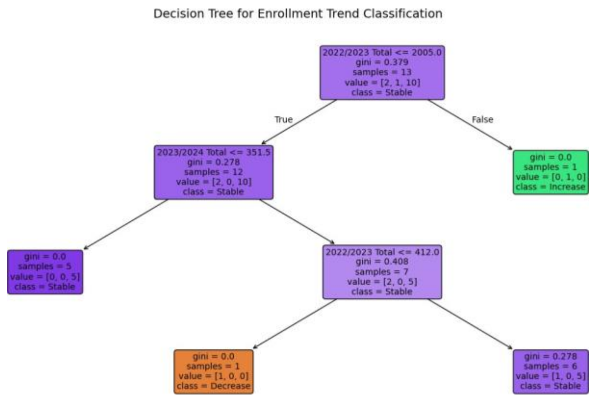

Fig. 4: Decision tree classification of faculty enrollment trends

Source: created by the authors.

4.5 Enrollment Forecasting

Looking ahead from 2025 through 2029, predictions for the Faculty of Medical Sciences rely on a basic linear approach. As shown in Figure 5, numbers keep climbing, indicating that more students want to enroll.

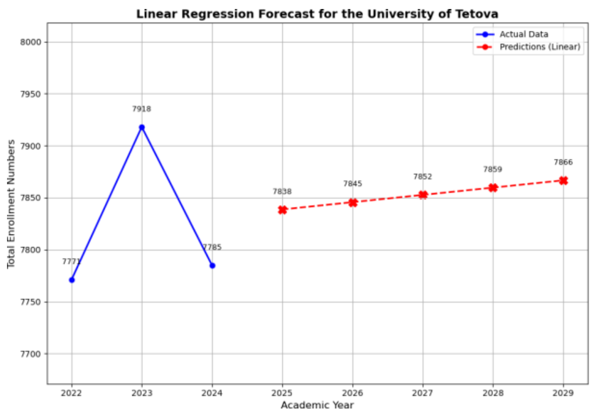

Fig. 5: Potential further growth

Source: created by the authors.

What we found gives clear clues for those shaping choices at colleges when it comes to spending, course design, or long-term direction. Watching who signs up over time turns out to matter, matching what is taught to what students want and where jobs are going.

4.6 Understanding How Algorithms Differ

Looking at how different machine learning methods com-pare (Table 1) shows they each bring something unique to this analysis. K-Means sorted faculties based on similarities in student numbers, clearly setting apart the Faculty of Medical Sciences as distinct. Because decisions need clarity, Decision Trees broke down trends into clear labels such as ”increasing,” ”stable,” or ”declining,” making patterns easier to grasp. Even though it lacks complexity, Linear Regression still delivered a clean forecast of future enrollments. On the other hand, stronger tools such as Random Forest or SVM might sharpen those predictions further.

4.7 Growth of the Faculty of Medical Sciences

Enrollments in the Faculty of Medical Sciences keep climb-ing, and this rise ties closely to the steady need for health workers worldwide. Job stability pulls many toward medicine, while social respect adds another layer of appeal. Instead of chasing uncertain paths, learners lean into roles seen as dependable, often leading to solid incomes. Gender patterns also show more women signing up than ever before, mirroring what is happening across medical schools globally.

4.8 Stable and Declining Faculties

Even fields such as Natural Sciences and Philology held their ground, hinting at a quiet but lasting pull among students. Yet certain social sciences saw fewer students each year; this may reflect shifting job markets, changing career appeal, or students drifting elsewhere. Watching where numbers rise or fall helps shape what gets taught and keeps departments from swelling too far or shrinking into silence.

4.9 Effects on How Universities Are Run

The results show how planning might shift at the University of Tetova. Growing numbers in the Faculty of Medical Sci-ences point toward needing more teachers and better facilities, as demand keeps rising. Where student counts stay flat, support should adapt without locking into fixed plans. When programs lose students, leaders may rethink their structure, refresh what is taught, or blend fields together differently. Using solid data helps UT match its courses to who enrolls and where jobs are going.

5 Conclusion

The numbers tell a clear story about where students choose to enroll. Starting with raw records pulled from university systems, researchers cleaned and shaped the information care-fully. After looking closely, patterns began showing up across departments. It turns out, year after year, one faculty stands apart. Even when different methods were applied, including sorting groups, predicting outcomes, and spotting shifts, the same result appeared: Medical Sciences consistently drew more applicants than any other field at the University of Tetova. Between 2021 and 2024, its lead did not shrink; it grew. Behind this trend lies something real: people want careers in health care, and society needs more doctors and nurses. Clear signals point to lasting interest, not just passing waves.

The analysis revealed multiple levels of understanding. Right away, looking at the data showed noticeable gaps between departments in how popular they were and who was enrolling. Grouping methods further highlighted that Medical Sciences did not follow the usual trend, standing apart while others settled into steady or shrinking paths. Sorting through decisions via tree models laid out straightforward conditions separating growth areas from those staying flat or fading, backing up what had already been seen. Finally, predicting numbers with linear trends pointed to an ongoing rise in Medical Sciences, shaping how institutions might prepare in the years ahead.

This work matters to the University of Tetova and schools like it. Growth areas, especially medicine, need focused sup-port: more teachers, better facilities, and updated courses. Where numbers stay flat or drop, attention must shift toward purpose, refreshing what is taught and blending subjects across fields. Balance here means using funds wisely without losing variety in what students can study.

This study has limits. Not every angle was covered, because only four years were examined, 2021 through 2024. Learners' backgrounds stayed out of view, along with their earlier grades or where they came from. National rules on schooling were not addressed either, nor was movement between regions. Yet still, for places like the University of Tetova, the findings hold weight. Fields pushing forward quickly, such as medicine, ask for more help, not just more instructors but stronger ones, better facilities, and updated lessons. In areas where growth stalls, the focus shifts toward why things are taught, not just how much. Old topics blend with new; subjects

cross paths unexpectedly. Smart spending keeps options open instead of narrowing choices down. Predictions here used linear regression, a method that is clear enough when patterns go straight, yet less effective when numbers shift in less predictable ways. Because of this gap, future work could turn to tools such as Random Forest or Neural Networks, letting researchers pursue closer fits. Gradient boosting is another option, though each step forward still depends on how well earlier methods acknowledge their limitations.

Going forward, the study will bring in more details, such as where students attended high school, where they live, and what happens after graduation. Instead of stopping at one institution, comparisons will extend to other colleges in North Macedonia and across the Balkans. The shifts seen at Tetova may not be unique, but rather echoes of wider regional movements. Looking into these links might uncover deeper forces shaping who goes where, giving schools better clues on how to adjust. With clearer pictures forming, guidance for universities may grow sharper and fit real situations more closely.

This work brings together institutional leadership ideas with number-crunching tools, showing how mathematical methods can help in areas usually based on opinion. Beyond looking at numbers alone, pattern-finding models also help spot trends in student numbers over time. When schools deal with rapid shifts, such as financial pressures or new technology, a method built on evidence makes long-term choices clearer. Instead of guessing, tracking patterns gives leaders better footing when shaping future steps.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

R. Sulejmanoska carried out the data collection, data pre-processing, coding of the machine learning models (K-Means clustering, decision tree classification, and linear regression), and drafted the original manuscript. F. Halili contributed to the conceptualization and design of the methodology and supervised the overall research process. M. Kasa Halili con-tributed to the statistical validation of the results and reviewed the manuscript. A. Rustemi contributed to the interpretation of the clustering and classification results and reviewed the manuscript. G. Xhaferi contributed to the literature review and reviewed and edited the final manuscript. All authors have read and approved the final version of the manuscript.

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