

## ✓ Project Title:

“Extracting Insights From University Data Using AI Powered Visualization”

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## □ Theoretical Background:

Universities create a large amount of data like student marks, attendance, faculty workload, and placement records. To understand this data, we need **visualizations** (charts, dashboards). But current tools like **Power BI and Tableau** need technical skills, are costly, and are not made for education data.

AUTOVI is a research system that shows how **AI can make visualization simple and automatic**. Its background is built on these main ideas:

1. **Data Cleaning (Preprocessing):**  
Raw data usually has missing or wrong values. AUTOVI cleans and prepares the data first so that the results are correct.
  2. **Automatic Visualization:**  
Instead of asking the user to choose charts, AUTOVI uses AI to **recommend the best chart automatically** based on the data.
  3. **AI for Insights:**  
AUTOVI uses a simple and clear AI model (MLP classifier). This helps in **finding patterns and insights** in data without working like a “black box.”
  4. **User Feedback:**  
Users can give feedback, and the system learns from it. This makes the tool more **interactive and adaptive** over time.
  5. **Easy for Everyone:**  
Because most of the work is automatic, even non-technical users like teachers or administrators can explore data without coding or BI tools.
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## 📋 What You Will Do

- **Collect University Data**
  - Gather data such as student marks, attendance, faculty workload, placements.
- **Automatic Preprocessing**
  - Clean data (handle missing values, errors, and formats) automatically.
- **AI Model for Insights**
  - Use machine learning (MLP/Decision Tree) to detect patterns, trends, and outliers.
- **Generate Visualizations Automatically**
  - Convert insights into charts and dashboards without Power BI or Tableau.

- **Interactive User Feedback**
    - Allow users (teachers, staff, admin) to give feedback (like/dislike visuals).
    - System improves recommendations over time.
  - **Build a Simple Interface**
    - A web-based dashboard where users upload data and instantly build result
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## □ Tech Stack (Example, not using Power BI/Tableau)

- **Database:** MySQL / PostgreSQL
  - **Preprocessing:** Python (Pandas, NumPy, Scikit-learn)
  - **AI Models:** MLP, Decision Tree, Random Forest
  - **Visualization:** Plotly, Matplotlib, Seaborn, D3.js
  - **Backend:** Flask / Django
  - **Frontend:** React.js / Chart.js / HTML-CSS-JS
  - **Deployment:** AWS / Heroku / Local Server
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## □ Expected Output

1. **Cleaned & Processed Data**
    - University data (students, attendance, faculty, placements) automatically cleaned and ready for analysis.
  2. **Automatic Visualizations**
    - System generates charts and dashboards (bar, line, pie, scatter, box plots, etc.) without using Power BI or Tableau.
  3. **AI-Extracted Insights**
    - Clear insights such as:
      - “Attendance dropped by 15% in Semester 4.”
      - “Female students performed better in Subject X.”
      - “Placement rate increased after 2022.”
  4. **Interactive Dashboard**
    - Web interface to upload data and view insights instantly.
  5. **User Feedback Integration**
    - Users can like/dislike visuals → system improves future recommendations.
  6. **Decision Support for Universities**
    - Helps administrators, faculty, and staff make data-driven decisions quickly and easily.
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## □ Novelty / What is New

| Feature                      | Existing Papers  | Your Project  |
|------------------------------|--|---|
| <b>Dataset / Domain</b>      | General tabular/business data (AdaVis, AUTOVI, DashBot, MultiVision)     | University data (students, attendance, faculty workload, placements)                    |
| <b>Preprocessing</b>         | Limited or manual (DashBot, MultiVision, CoInsight)                      | <b>Automatic preprocessing</b> of raw university data (missing values, noise, encoding) |
| <b>Visualization</b>         | Recommended charts/dashboards using ML/DL (AdaVis, MultiVision, DashBot) | <b>Automatic chart generation</b> directly from university data                         |
| <b>Insight Extraction</b>    | Basic patterns (AUTOVI, Waltzboard)                                      | <b>Detailed insights:</b> trends, comparisons, outliers, student/department performance |
| <b>User Feedback</b>         | Limited or absent (DashBot, Waltzboard)                                  | <b>Interactive feedback loop</b> (system improves with likes/dislikes)                  |
| <b>Explainability</b>        | Some works provide local/global explanations (AdaVis)                    | <b>Clear insight explanations</b> + justification for chosen visuals                    |
| <b>Domain-Specific Focus</b> | Mostly generic or business-oriented dashboards                           | <b>Focused on higher education analytics</b>  |
| <b>Outputs</b>               | Visuals only (CoInsight storytelling, MultiVision dashboards)            | Visuals + <b>AI-driven insights</b> + <b>feedback adaptation</b>                        |
| <b>Ease of Use</b>           | Medium (require some technical knowledge or iteration)                   | <b>High</b> (any staff can upload data and get results instantly)                       |

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## □ Example Flow

Nice — here's a **clear, step-by-step, detailed explanation** of how **AUTOVI** works (so you can use it in your report). I keep language simple and add exact references to the paper where useful.

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[How AUTOVI works — detailed walkthrough](#)

## High-level idea (one line)

AUTOVI is a web platform that **automatically cleans tabular data, scores which visuals fit each column, generates visualizations, explains them, and learns from user feedback.**

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## 1) Data & dataset preparation

- The authors collected **many real datasets** (25 Kaggle datasets with varied sizes/types) to cover real-world cases. An automated process extracts dataset **metadata** (column names, types, counts, null rates, distributions).
  - For training the recommender they **added a “visualization label” column** and populated it (manually, from expert guidance) so the model had examples of which chart is appropriate for which column. This mimics **how humans** label charts.
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## 2) Automatic preprocessing (what it does)

When a user uploads a file, AUTOVI runs an automatic cleaning pipeline that includes:

- **Data type detection** (numeric / categorical / temporal).
- **Null/missing value handling** (reporting counts and applying imputation or exclusion as needed).
- **Standardization / scaling and encoding** (one-hot for categoricals, numeric scaling) so features are ready for ML.
- **Outlier / noise detection** and basic corrections so visuals aren't misled by bad rows.
- The system also builds a **profile report** (column distributions, correlation matrix) so users see dataset health and characteristics.

In short: AUTOVI fully prepares the table automatically so downstream models and visuals get clean inputs.

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### 3) Feature extraction / metadata used by the model

AUTOVI computes per-column features such as: data type, cardinality, null count, min/max/mean, distribution shape, unique values, etc. These become the input features for the visualization classifier.

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### 4) The visualization classifier (the ML core)

- AUTOVI uses a **transparent Multi-Layer Perceptron (MLP)** as its core classifier to predict which visualization suits each column.
  - **Architecture (paper)**: input layer (column features) → **two hidden layers** with ReLU → output layer with **sigmoid** to give probabilities for visualization types.
  - **Training details** reported: binary cross-entropy loss, Adam optimizer, batch size 32, feature scaling and one-hot encoding used in preprocessing. The MLP classifies into types like **histogram, binned histogram, bar chart, or none** (non-informative).
  - The paper reports ~**90% accuracy** on their prediction task (on their prepared datasets).
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### 5) Mapping model output → actual visualizations + explanations

- The MLP outputs probabilities for visualization types per column. The system maps the top prediction(s) to **visualization templates** (Plot: histogram, bar, line, box, etc.) and creates the chart.
- AUTOVI also **generates explanations**: it shows why a chart was chosen (e.g., “column has numeric values and low cardinality → bar recommended”) to build user trust. The explanation module is part of the Identify Visualization module.

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## 6) Interactive UI modules (user-facing features)

AUTOVI's platform is modular and user-friendly; main UI modules include:

- **Upload dataset** (auto triggers cleaning).
  - **Features Module** (shows column types, distributions).
  - **Identify Visualization Module** (automatically recommends + explains).
  - **Try Your Own Visualization**: users can pick a column + chart type to try; the system gives hints/feedback (if the selection is suboptimal it explains why). This produces active learning and better user understanding.
  - **Profile Report Module**: a summary page (statistics, correlation heatmap) for quick dataset insight.
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## 7) User feedback & learning loop

- AUTOVI captures user interactions (likes/dislikes, corrections from “Try Your Own”) and uses that feedback to **improve the system** (retrain models, refine recommendations). The paper highlights dynamic feedback mechanisms and that the platform is meant to be iterative and learn from users.
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## 8) Model training & offline improvements

- The **Model Training Module** supports retraining (using the labeled examples + user feedback/provenance). The system is designed so model updates can be applied as more labeled data or feedback accumulates.
  - Note: initial supervised training needed the manual “visualization label” column (authors created these labels during dataset preparation). After deployment, feedback can reduce the need for manual labeling over time.
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## 9) Evaluation & user study (what the authors measured)

AUTOVI was tested vs manual coding; results show strong usability and efficiency:

- **Time**: AUTOVI average time  $\approx$  **3.7 minutes** vs traditional coding  $\approx$  **43.25 minutes**.
- **Usability (SUS)**: AUTOVI scored  **$\sim$ 82.66** (excellent usability).

- **Engagement and workload (TLX)** results also favored AUTOVI strongly; the paper reports statistically significant differences.
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## 10) Limitations & future work (from the paper)

- AUTOVI authors note limits: adapting to very diverse datasets, adding more visualization choices per column, and supporting real-time visualizations are areas for future improvement. They emphasise continuing user testing and domain expert collaboration.
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### Short sequence view (step-by-step flow)

1. Upload CSV/Excel → 2. Auto preprocess (type detection, missing values, encoding) → 3. Extract per-column features → 4. MLP predicts best viz type → 5. System builds chart + explanation → 6. User views/tries/feedbacks → 7. Feedback logged → 8. Retrain / refine model offline → repeat.
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### Quick notes for your project (how to use AUTOVI ideas)

- Reuse AUTOVI's **automatic preprocessing** → **feature extraction** → **MLP classifier** → **mapping to viz templates** → **feedback loop** design for your university data.
  - For university domain, extend features with **domain signals** (semester, course type, grade scale) and include specialized visuals (boxplots for grade distributions, heatmaps for attendance). The AUTOVI pipeline makes adding domain features straightforward.
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## 🔄 What Is New in Your Project (Compared to Published Papers):

| Paper                              | Input Modalities                           | Model Type   | Dataset                             | Accuracy / Eval                                | Key Contribution  |
|------------------------------------|--|--|-------------------------------------|--|---|
| <b>AdaVis (Zhang et al., 2024)</b> | Tabular data (columns & metadata)          | Graph Neural Network (GNN) + Explainability Module               | OpenML datasets                     | ~83–92% accuracy (on visualization prediction) | Adaptive & explainable visualization recommendation using GNN               |
| <b>AUTOVI (2024)</b>               | Tabular datasets (CSV/Excel)               | Multi-Layer Perceptron (MLP) classifier + preprocessing pipeline | 25 Kaggle datasets                  | ~90% accuracy                                  | Automatic preprocessing + visualization recommendation + user feedback loop |
| <b>DashBot (2023)</b>              | Tabular datasets (structured data)         | Deep Reinforcement Learning (A3C Agent)                          | Synthetic & real datasets           | Policy reward scores (not accuracy)            | Insight-driven dashboard generation using RL                                |
| <b>MultiVision (2022)</b>          | Tabular data (query + visualization pairs) | Siamese Neural Network   | VizNet dataset                      | Precision/Recall ~78–85%                       | Analytical dashboard design using similarity learning                       |
| <b>CoInsight (2024)</b>            | Hierarchical tables                        | Graph-based Insight Graph Construction                           | Real-world hierarchical tables      | User study (positive storytelling outcomes)    | Converts tables into <b>visual stories with connected insights</b>          |
| <b>Waltzboard (2022)</b>           | Multi-criteria dashboard inputs            | Rule-based + Optimization model                                  | Case studies (Exploratory analysis) | User evaluation                                | Multi-criteria <b>automated dashboard design</b>                            |
| <b>VIS+AI (2023)</b>               | Tabular datasets                           | AI-guided Visualization Framework                                | Multiple (case studies)             | Qualitative evaluation                         | Framework for integrating AI with visualization for <b>explainability</b>   |



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## 🔍 What You Will Improve

- Domain Focus** → AUTOVI is general; yours is **specific to university data**.
- Richer Insights** → **Not just charts, but trends, comparisons, outliers.**

3. **Better Explainability** → Explain not only *why this chart*, but also *why the insight matters*.
4. **Stronger Feedback Loop** → System **learns continuously** from user feedback.
5. **More Visual Types** → Add **heatmaps, boxplots, correlation plots** for education data.
6. **Automatic Reports** → Generate **summary reports + visuals** for decision making.