



AI-Powered Automated Data Visualization and Fairness Analysis Platform

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Abstract: The Problem is that as data analytics for analysis the data we need to use the various tools like Power BI, Tabulate for Visualization. Also, in excel we analyze the data and visualize also. There is a tool to analysis the data but the checking of fairness in data and bias in dataset this tool is not support. The making AI powered Automated data visualization and fairness Analysis platform. It helps the platform to in HR, Healthcare, Finance. The Platform aim to that we fair all the Employees in company, the loan approval in bank. To check the statistics automatically no need to calculated separately.

Keyword: Fairness in ML, AI Visualization Dataset, Automated Analytics, Detect Bias and Fairness

I. INTRODUCTION

When uploaded the dataset it automated visualization directly. The growth of data in fields such as finance, healthcare, and education has made manual data visualization increasingly inefficient. As AI-driven analytics platforms evolve, users demand systems that not only visualize complex data but also ensure fairness, transparency, and interpretability in automated decision-making processes. Automated Data Visualization and Fairness Analysis Platforms combine AI automation and ethical intelligence, enabling users to upload datasets and instantly generate visual dashboards while detecting potential bias or unfair treatment among attributes such as gender, race, or age.

The AI-automated it easily analysis the dataset in large amount in the HR, Healthcare, finance field. AI systems to summarize large datasets, reveal hidden trends, and support decision making. Despite these advancements, challenges related to fairness, transparency, and bias have gained big attention. Automated systems often inherit the bias from underlying datasets, resulting in unfair outcomes or misinterpretations. Therefore, combining AI-based visualization with fairness analysis becomes essential to ensure both performance and ethical responsibility. It also helps to easily understand the patterns of the dataset.

Algorithmic fairness is a relatively new research field in AI/ML but has rapidly gained increasing attention in recent years. A classic example of algorithmic bias comes from the Correctional Offender Management Profiling for Alternative Sanctions (COMPAS), a tool used by courts in the USA to identify the risk of a person recommitting another crime [1].

The justification is rather the explanation of what AI algorithms do with the data, which is to learn and extract patterns from the data. Should the data, for example, contain favoritism towards a group of a protected attribute (e.g., race), then this bias will manifest and propagate in the learned parameters and eventually in the output [2].

In the large data it complicated to analysis it faces the challenges when it scales the large amount of data.

II. LITERATURE SURVEY

Several studies have examined the intersection of data visualization and fairness in AI systems. The research articles VIS+AI: integrating visualization with artificial intelligence for efficient data analysis highlights explainable visualization methods. Similarly, Journal of Biomedical Informatics the research that says the A scoping review of fair machine learning techniques when using real-world data surveyed fairness-aware machine learning techniques focusing on pre-processing, in-processing, and post-processing bias mitigation and detection.

In visualization automation, tools such as Power BI, Tableau AI, they recommend charts or summarize insights automatically. However, they rarely evaluate fairness or bias detection. Recent academic contributions propose fairness dashboards that visualize bias across gender, race, or region, allowing analysts to interpret model behavior transparently. Fairness in AI has been studied extensively through frameworks like IBM AI Fairness 360 (AIF360), Fair learn. This literature suggests that while automated visualization is advancing rapidly, its combination with fairness auditing remains an emerging research field, emphasizing the importance of this integrated platform.

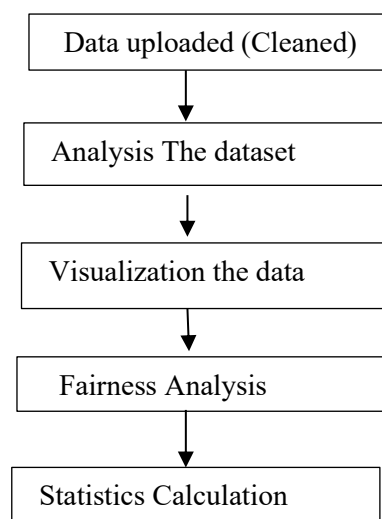


The detection of bias and fairness in dataset it the AI model decision such prediction, classification and recommendation. Fair and bias is help that disadvantages and unjustified for some group of peoples like gender race, age, religion or some status. AI system learns from data which we provide to them. If the data is bias AI model also learn from it.

Examples in Company if an AI model system is trained mostly on data about men for job application, it might unfairly reject the application of qualified women. If the facial recognition system is trained mostly on brighter skin tones, it not work well for peoples with darker skin. It also the unfairness with skin color. For also in bank loan when the income for the employee is less than they have to want the loan from bank. Some condition of the bank employee will not fulfilled the rules of bank loan for some personal and financial reason, that time it unfair to those employee which is not completed their requirements.

III. METHODOLOGY

A. System Architecture:



B. Workflow:

- Step - I: Data uploaded (CSV, JSON, etc).
- Step – II: Preprocessing, In-processing, Post processing.
- Step -III: Automated Visualization
- Step – IV: Fairness analysis
- Step – V: Bias Detection
- Step – VI: Suggestion
- Step – VII: Analysis Report downloaded.

C. Its system work on the two model:

We searched about the various methodology and algorithms in this we are work on two methodology which are they are automated data visualization (AutoViz Engine) and Fairness analysis.

a) Automated Data Visualization:

When data uploaded the dataset on system it automatically generated the visualization from useful insights. Identify the data pattern and data distribution, correction of the data. By using the Plotly, seaborn, it generate the Interactive charts for visualization.

b) Fairness Analysis:

When the fairness analysis it detect the bias across sensitives attributes like the data of gender age, race.

It specifies the sensitive interface in the data. To checking the favoritism in data of employee. Fairness is That to detecting the problem in data, to analysis the problem getting useful output from the data.

We fixing the fairness in data the using of the libraries such as AIF360 and Fairlearn. These libraries help to fixing the fairness and bias detection in dataset.

**IV. FINDINGS AND TRENDS**

Study of the fairness visualization it collects the data from dataset which provides the AI system. The findings the patterns of the data. AI for visualization is used the knowledge generation process in data visual analysis can benefit from AI. Already existing the studies of AI approaches the findings, action, insights from dataset. For human beings lack the big data from different dimensions and identify the big data charts of visualization of data. It's very difficult to finds the perspectives of the data. Fortunately, AI Approaches the large amount of data patterns and identify the significant of the large data. Visualization of large amount of dataset with AI platform its really goods for saving the times to define the patters, format, process, etc.

In this studies the findings

- 1) recommending appropriate visual representations to facilitate finding identification, and
- 2) recommending findings by simulating finding identification behaviors of humans.

Recent advancements between explainable AI and automated visualization includes generative AI models for visual recommendations, for fairness transparency it used the explainable AI dashboard, for checking the bias detection and fairness there is data used the libraries of AIF360 And Fairlearn.

A. Key Trends:

1. Rising of AutoViz Systems: Automation tools like AutoViz have made visualization generation faster,
2. Fairness Dashboards: Major AI toolkits Microsoft's Fairlearn incorporate fairness visualization to detect.
3. Explainable Dashboards: Platforms include the layers to translate complex outputs into human-understandable visuals.
4. Natural Language to Visualization (NL2VIS): AI models convert text queries into charts, simplifying analytics for non-technical users. Anyone new user can easily understandable.
5. Cloud-Based AI Visualization: The Distributed architectures allow real-time data visualization and fairness monitoring on scalable infrastructures.

B. Challenges and Gaps:

1. Bias in Training Data: Even fairness-aware systems can replicate biases inherent in data.
2. Complex data Interpretability: Explaining AI fairness decisions remains difficult for non-experts.
3. Computational Data Overhead: Real-time fairness visualization requires high processing power.
4. Lack of Standardization: No universal fairness visualization standard exists across tools.
5. Data Privacy: Handling sensitive data raises challenges with GDPR and related regulations.

Studies show that fairness visualization improves user trust and helps identify systemic issues in data collection and modelling processes. Platforms combining automation and fairness can empower organizations to maintain compliance with AI principles. To detect bias and fairness in data improve the data quality and collection faster and visualize the data in proper way.

V. CONCLUSION

To study of the AI automated platform of data visualization its direct communication between Human Intelligence and AI Intelligence. AI system is help to visual analysis from the perspective of knowledge Extraction processes, with the help of AI visualization to inspire the new studies.

Fair in data of the Healthcare, HR, Finance which improves the quality of data, and understanding the patterns, processing and selection of the dataset. For fairness analysis which help in the HR, Healthcare, And Finance to provides the equality in gender, race, age. Etc. AI-powered visualization tools have significant with fairness assessment and transparent communication between human intelligence and AI intelligence. Ensure that data visualization serves the both analytical accuracy and social fairness with further development in AI Automation platform.

VI. FUTURE DIRECTION

The beneficial in future that we easily understanding the analysis the patterns of the data. High-quality training data describes the analysis behavior of humans is support to AI learning from humans.

There are various things to summarize the data in future direction to develop the visualization with AI

- a) Understanding the analysis behavior of data: with the help of AI automated platform, we easily define the behavior of training data in dataset when we uploaded to analysis.



- b) Collecting analysis provenance: Previous analysis data we easily seen the processes and patterns of data, the repeating data view AI easily recognized the data within a time. AI system understands the design and constructs the data from previous case study.
- c) Ensuring the data security: In recent development security is priority to all when the AI needs to secure all our data which was we provided to analysis. It prevents from unauthorized user who is not stole the data. It maintains the privacy of user and AI models have to be transparent and explainable between the users.
- d) Visual knowledge Expression: Based on visualizations designed by humans, AI has learned to select the appropriate visual encodings for data in sample format. Common charts such as bar charts, line charts, columns charts, pie charts, can be generated according to data characteristics and user preference Automatically.
- e) AI Reliable: AI model is allowed to take all responsibility for simple mission such as face recognition, gender equalities its quit possibles but we need to understand these things when we provide to dataset to AI system, we need to check the data is fully cleaned or not because AI learns from data when we provided the data with not reliable the patterns get the AI in wrong way. We overcome the data must have the provided with accurately.

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