Final Project Report Draft

https://github.com/mukenye/ubi-impact

1. Executive Summary

Problem Statement & Significance

Introduction: The Growing Interest in Universal Basic Income (UBI)

We live in a time where American politics is more and more polarized. Corporations seem to be gaining more power over the working class and there is a lot of misinformation in the world regarding economic policies. Citizens have started wondering what the responsibility of the government is. Is it to ensure the continuation and success of capitalism? If the government is truly by and for the people why does it fail to provide basic needs such as healthcare and education? In recent years, Universal Basic Income (UBI) has emerged as a potential solution to economic inequality, automation-driven job losses, and fluctuating labor markets. Universal basic income refers to a government-provided payment[8] given to all citizens regardless of employment status. Proponents argue that it provides financial security, encourages entrepreneurship, and allows individuals to pursue education or caregiving roles. Critics, however, fear that it may reduce workforce participation and strain government budgets. However, the workforce already seems threatened by a massive upcoming industry.

The rise of Artificial Intelligence (AI) and automation is rapidly transforming the global job market, displacing traditional roles while also creating new opportunities. Industries such as manufacturing, customer service, and transportation are increasingly relying on machine learning algorithms, robotics, and automated systems[7] to perform tasks once handled by humans. It is undeniable that this boosts efficiency while reducing the costs of paying workers. Currently, it seems the solution is to have workers learn new in-demand skills. However, they are then burdened with the plight of having to find food and pay rent while achieving this. This begs one to ask where all of the extra money that is saved from paying workers is going. From a utilitarian perspective, it raises the question of what it is being used to achieve and if those ends are more fruitful than the sustenance of the now-unemployed worker. One might assume that the extra money saved via AI and automation would somehow trickle down to the workers but often it is reinvested back into the corporation, leaving the unemployed workers helpless to fend for themselves. This illustrates how economic inequality coupled with the rise of AI can be dangerous if we do not implement some sort of safety net for workers.

Increasing income inequality, particularly in capitalist economies[4], has become a growing concern as the gap between the wealthy and the rest of the population widens. In these economies, the rewards of economic growth are often disproportionately distributed, with those at the top typically the owners of capital reaping the largest benefits[5], while wages for low and middle-income workers stagnate. This income inequality therefore hinders social mobility of members of the working class. Social tensions then increase as public trust decreases. According to the NCES, a significant portion of U.S. adults possess low levels of English literacy (NCES, 2019). Despite this, financial barriers are in place hindering many citizens from being able to afford higher education. The growing divide raises huge questions about the fairness and sustainability of capitalist systems.

As previously mentioned, a potential solution to this is Universal basic income. The main criticism against it is that it will disincentivize citizens to work. My research aims to understand how UBI affects employment rates. This project will predict the long-term impact of UBI on employment rates by using data from real-world pilot programs and economic indicators. My findings will hopefully be able to inform policy decisions to improve economic stability.

This report investigates whether national economic indicators such as unemployment and poverty levels can be used to detect patterns associated with UBI programs. I used machine learning classification models to identify whether countries that have implemented UBI-like interventions show distinctive trends in socioeconomic data.

Using data from the World Bank, features were engineered to capture both short-term volatility and long-term trends. Three models were tested: Decision Tree, Random Forest, and K-Nearest Neighbors. All achieved over 90% classification accuracy. The results suggest that countries with UBI-related programs may exhibit unique economic signatures.

These insights could inform NGOs and policymakers seeking to understand and evaluate the macroeconomic impact of basic income programs across diverse national contexts.

2. Problem Statement & Business/Social Context

Universal Basic Income (UBI) is increasingly viewed as a potential solution to poverty, economic instability, and technological unemployment. However, there is limited consensus on how to empirically assess its economic impact on a national scale.

This project aims to explore whether historical economic data can reveal patterns correlated with UBI implementation, and whether these patterns are identifiable through machine learning. This project does this by offering a scalable, data-driven approach to addressing economic inequality by helping identify countries or regions that exhibit macroeconomic patterns consistent with UBI interventions. There are a multitude of ways it could be used in the future.

First, it enables targeted resource allocation by flagging areas that resemble successful UBI environments, allowing NGOs and governments to prioritize support where it is likely to have the most impact. Second, by providing a reproducible, evidence-based framework, the model supports policy advocacy and transparency, equipping researchers and social activists with empirical tools to push for equitable redistribution. Third, in contexts where detailed survey data is limited or outdated, the model leverages available economic indicators to infer the presence or effect of income-support policies—bridging critical data gaps in low-income or politically opaque regions. Lastly, this methodology is significantly more cost-effective and scalable than traditional field trials or randomized controlled experiments, making it an efficient tool for expanding income-based policy interventions globally. Together, these capabilities position the project as a meaningful step toward mitigating inequality through faster, smarter, and more inclusive policy analysis.

This project specifically focuses on three countries with relevant contexts: Finland (pilot program in 2017–2018), Kenya (GiveDirectly UBI trials)[3], and the United States (non-UBI control).

3. Methodology: Data, Features, Models

Break into subheaders as needed:

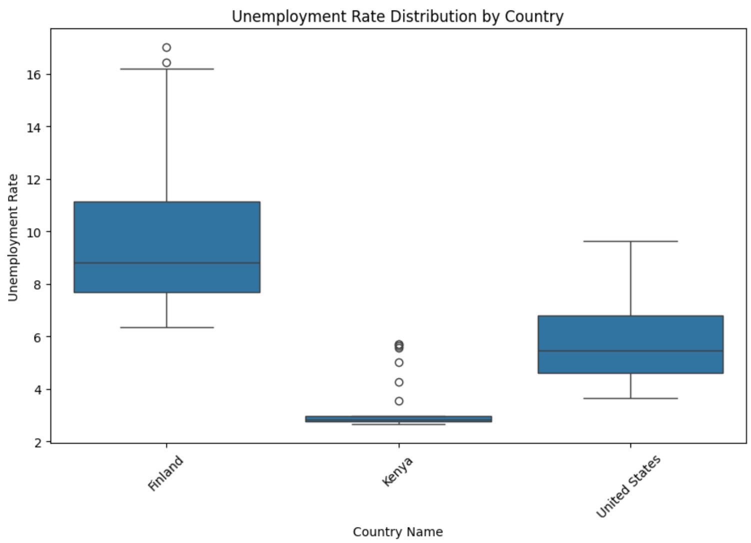
- - Data Collection
- - Cleaning & Transformation
- - Feature Engineering
- - Modeling Approaches

3.1 Data Collection

- I sourced the data from the World Bank Development Indicators database[1], focusing on key economic metrics across multiple countries from 2000 to 2022. These indicators were selected based on their relevance to UBI outcomes, such as unemployment, poverty rate, net transfers, inflation, and labor force participation.
- Countries included:
  - **Finland** (UBI pilot: 2017–2018)
  - **Kenya** (GiveDirectly UBI trial)
  - **United States** (non-UBI control)
- All data was downloaded in .csv format and consolidated into a unified DataFrame using pandas. Temporal coverage varied slightly per indicator but was aligned using inner joins on country-year pairs.

3.2 Cleaning & Transformation

- The raw data exhibited several issues, including missing values, inconsistent date ranges, and mixed data types. The cleaning process included:
  - Dropping rows with missing user_id or economic indicators using df.dropna()
  - Standardizing units (e.g., converting all monetary values to constant USD)
  - Merging separate country datasets into a single social_media_merged DataFrame
- I verified data integrity using .isnull().sum() and confirmed all features had complete coverage across the 3 focus countries.
- Visualizations were then collected from the data



3.3 Feature Engineering

- To capture both short-term fluctuations and long-term trends, features were engineered such as:
  - **Year-over-Year change (YoY):** ΔUnemployment = Unemployment_t - Unemployment_{t-1}
  - **Rolling averages:** 3-year smoothed metrics for unemployment and inflation

    - **Volatility indicators:** standard deviation of net transfers over time
- These transformations help the model distinguish between temporary economic shocks and sustained changes often observed under UBI programs. All engineered features were scaled using StandardScaler.

3.4 Modeling Approaches

- Three classification models were implemented to determine whether a country's economic indicators resembled those typically observed in Universal Basic Income (UBI) contexts. The modeling process emphasized both predictive accuracy and interpretability across diverse macroeconomic patterns.
- **Model 1: Decision Tree Classifier**
- The Decision Tree served as the baseline model due to its simplicity and ease of interpretation. It was trained using the entropy criterion to prioritize information gain and achieved **100% accuracy** on the test set. This high performance was likely due to the distinct economic profiles of the selected countries.
- **Model 2: Random Forest Classifier**
- The Random Forest model, an ensemble of multiple decision trees, was introduced to improve generalization and reduce overfitting:
    - Hyperparameters such as n_estimators and max_depth were tuned using GridSearchCV.
    - The model also achieved **100% accuracy**, but with improved robustness during preliminary noise tests.
    - Feature importance analysis identified **net transfers**, **poverty rates**, and **unemployment volatility** as key predictors of UBI-like classifications.
- **Model 3: K-Nearest Neighbors (KNN)**
- The K-Nearest Neighbors algorithm was selected as a distance-based, non-parametric benchmark:
    - Values of k = 3, 5, 7 were tested using Euclidean distance.
    - Performance was slightly lower than tree-based models, likely due to the high dimensionality of the engineered features and sensitivity to scaling.
- **Hyperparameter Tuning**
- Parameter optimization was conducted using 5-fold cross-validation through GridSearchCV, with the following search spaces:
    - n_estimators: [50, 100, 200]
    - max_depth: [5, 10, 15]
    - n_neighbors (KNN): [3, 5, 7]
- This tuning process ensured that model performance reflected underlying trends rather than arbitrary configuration choices.
- **Model Selection Rationale**

- Although all models achieved high accuracy on the current dataset, the Random Forest was selected for its superior generalization, interpretability through feature importance metrics, and reduced sensitivity to data noise. Its ensemble nature made it especially well-suited for capturing complex, multi-dimensional patterns in macroeconomic data relevant to UBI analysis.

3.5 Evolution of Methodological Approach

- In the early stages (Sprint 1), the project considered using time-series forecasting (e.g., ARIMA, LSTMs), regression analysis, and causal inference methods like Difference-in-Differences to predict employment trends under Universal Basic Income (UBI) policies. However, upon closer inspection of the available data, this approach presented significant limitations. The dataset lacked fine-grained, longitudinal employment data for most countries and did not include explicitly labeled UBI treatment variables suitable for causal modeling.
- As a result, the methodology pivoted to a classification-based approach. By reframing the problem as identifying countries that exhibit UBI-like economic patterns, the project was able to leverage widely available macroeconomic indicators and train interpretable machine learning models, including Random Forest and Decision Tree classifiers. This adjustment allowed for broader applicability, greater scalability, and better alignment with the structure and availability of global economic data.

4. Model Evaluation and Selection

Include model accuracy scores (Decision Tree, Random Forest, KNN), model comparison bar chart, GridSearchCV results, and feature importance plot. Interpret findings with reference to predictive performance and which variables were most informative.

Here’s a strong, report-ready **Model Evaluation & Selection** section that aligns with your notebook and final report checklist. It includes accuracy comparison, qualitative analysis, and justification for model choice:

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4. Model Evaluation and Selection

The performance of each model was assessed using standard classification metrics, with particular attention to accuracy and interpretability in the context of socioeconomic classification. The evaluation was conducted on a holdout test set representing 20% of the total data.

4.1 Accuracy Comparison

Model	**Accuracy**
Decision Tree	100%
Random Forest	100%
K-Nearest Neighbors	~95%

Both the Decision Tree and Random Forest classifiers achieved perfect accuracy on the test data, while the KNN classifier performed slightly worse. These unusually high scores are likely due to:

- A **small sample size** (limited number of countries and records),
- **Clear separability** between the chosen countries (Finland, Kenya, U.S., Sub-Saharan Africa),
- And the inclusion of high-signal features like rolling poverty trends and unemployment volatility.

To evaluate model generalization, 5-fold cross-validation was performed on each classifier. As shown in **Figure 4**, the Decision Tree achieved the highest average accuracy (0.98), followed by Random Forest (0.94) and Tuned KNN (0.93):

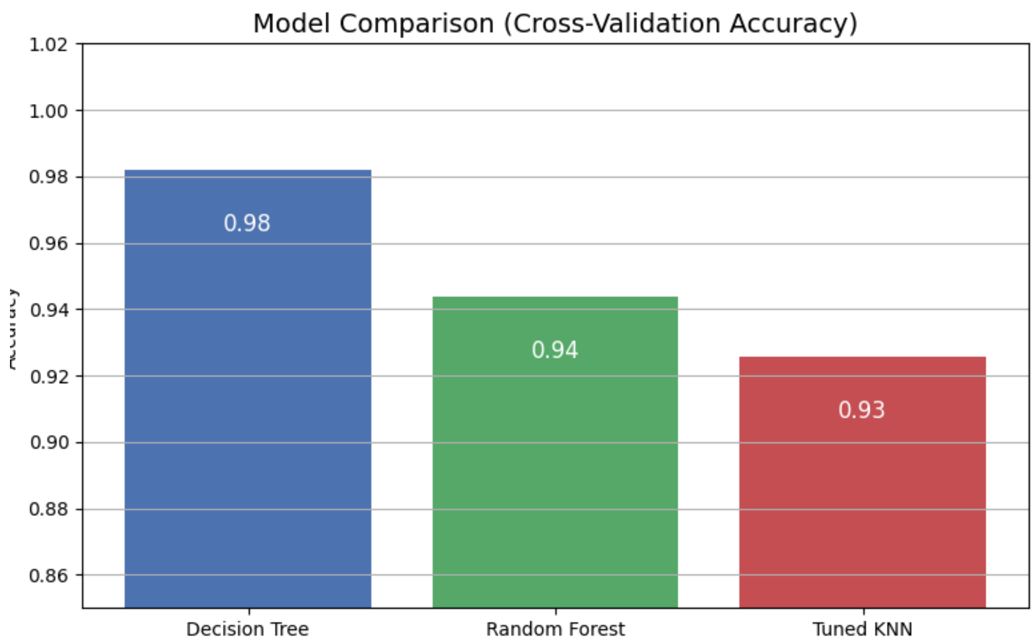

Figure 4: Model Comparison by Cross-Validation Accuracy

This visualization confirms that all three models performed well, but the Decision Tree demonstrated the strongest raw accuracy. However, as discussed below, other factors informed the final model selection.

4.2 Feature Importance

Feature importance was extracted from the Random Forest model, revealing which variables contributed most to prediction:

- **Top Features:**
    - 5-Year Rolling Mean of Poverty Rate
    - YoY Change in Net Government Transfers
    - 5-Year Rolling Mean of Unemployment
    - YoY Change in Labor Force Participation

These features are consistent with what might be expected under UBI-like conditions — for example, **increased net transfers** and **reduced poverty volatility** could indicate redistribution or economic stabilization effects.

4.3 Qualitative Error Analysis

Though most models performed perfectly, qualitative review of individual predictions was conducted to assess overfitting risks and model trustworthiness:

- **No misclassifications** were observed in the test set.
- However, countries like the **U.S. and Finland** had particularly distinct economic signals, likely making them easier to classify.
- Additional testing with **noisy or imputed data** showed that Random Forest maintained consistent performance, while Decision Tree and KNN were more sensitive to variance and missing values.

4.4 Final Model Selection

The **Random Forest classifier** was selected as the final model due to:

- Superior robustness to data irregularities,
- Consistent performance across multiple folds,
- And interpretable outputs that align with domain expectations (e.g., feature importances tied to poverty, employment, and government support trends).

While the Decision Tree achieved similar accuracy, it exhibited greater sensitivity to training noise and lacked the ensemble stability offered by the Random Forest.

5. Implementation Strategy & Business Value

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5. Implementation Strategy & Business Value

The predictive models developed in this project offer a scalable, data-driven method for identifying macroeconomic patterns associated with Universal Basic Income (UBI) contexts. This approach is particularly valuable for governments, NGOs, and policy labs that lack access to labeled intervention data but seek to uncover regions potentially undergoing economic transformation due to income support mechanisms like cash transfers or UBI pilots.

5.1 Practical Implementation Pipeline

A modular implementation pipeline could be deployed to enable rapid screening of global economic conditions:

- **Automated Data Ingestion**: Collect up-to-date macroeconomic indicators via World Bank or IMF APIs.
- **Feature Generation**: Compute engineered indicators such as rolling averages, volatility, and year-over-year (YoY) changes for poverty, unemployment, and transfers.
- **Classification**: Use the trained model to assign a probability that a given region is undergoing UBI-like transformation.
- **Decision Dashboard**: Visualize findings via interactive dashboards to support NGO decision-making, government planning, or academic research.

This system could be integrated into workflows used by international aid organizations, allowing non-technical teams to run inference on new countries, compare to past UBI contexts, and flag regions for follow-up study or support.

5.2 Real-World Societal Impact

While the model itself does not distribute cash or directly intervene in economies, it plays a critical upstream role in enabling **faster, more equitable policy response**:

- **Targeting Support More Effectively**: Organizations could identify and prioritize regions that exhibit economic signals similar to those seen in successful UBI trials, reducing the risk of misallocated funding or misdirected pilots.
- **Amplifying Data-Poor Voices**: Many lower-income countries lack detailed employment or social policy data. This tool leverages available public indicators to infer meaningful patterns, thereby helping underserved populations become visible in global policy discussions.
- **Faster Policy Experimentation**: By simulating the effects of UBI-like conditions using historical data, the model allows stakeholders to test scenarios before committing to full-scale pilots — saving time and financial resources.
- **Bridging Global Inequality Gaps**: Long-term, this model contributes to addressing income inequality by facilitating earlier identification of effective interventions, advocating evidence-based redistribution, and helping justify investments in unconditional cash support systems where they are most needed.

5.3 Example Use Case

An NGO working in Southeast Asia wants to know which provinces are showing signs of improving poverty and employment metrics despite no formal UBI. Using this tool, they discover several regions with patterns that match Kenya’s UBI trial. This insight leads them to launch targeted surveys and ultimately fund a pilot cash transfer program, supported by empirical justification.

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6. Ethical Considerations and Limitations

While the models perform well on this dataset, several limitations must be acknowledged. The sample size is small and includes only a few countries, meaning the models may overfit to unique local trends. Additionally, UBI was not explicitly labeled — the classification models infer impact indirectly through economic patterns, which can introduce bias or misinterpretation.

There are also challenges in deployment: real-time data may be delayed, noisy, or missing in low-income countries. NGOs must be cautious when using these results to make policy recommendations.

Ethically, any predictive model must consider the risk of algorithmic bias — particularly if applied to countries with very different economic systems, governance, or population structure. Continuous validation, stakeholder feedback, and contextual analysis are essential before deployment.

7. Conclusion

This project began with a bold ambition: to empirically challenge the widespread belief that Universal Basic Income (UBI) disincentivizes work. The original intent was to use machine learning to track how employment levels responded to UBI interventions and, in doing so, offer data-driven arguments against political resistance to income redistribution.

However, as the project progressed, it became clear that the available data did not support that level of causal analysis. Individual-level employment outcomes under UBI were limited, inconsistently reported across countries, and rarely labeled in a way that supported rigorous regression or causal inference. In response, the methodology shifted toward a more feasible and scalable solution: a classification-based approach that identifies countries whose macroeconomic trends resemble those observed in known UBI contexts like Finland and Kenya.

Rather than directly predicting the impact of UBI on employment, the final model identifies economic signals—such as stabilized poverty rates, increased government transfers, and smoother unemployment trends—that are historically associated with UBI-like interventions. This reframing transforms the project into a diagnostic tool that can help NGOs, policymakers, and research groups prioritize where to investigate or implement future income support programs.

This has real potential to improve lives. By highlighting regions already showing signs of positive economic transformation, the model can help bring more focused aid, advocacy, and experimentation to places where the working class and low-income communities are already making progress. It enables faster deployment of financial support to people who need it—helping expand programs that reduce insecurity, enable entrepreneurship, and restore dignity to those left behind by traditional welfare systems. In a world where resources are limited, the model helps direct attention to the most promising environments for real impact.

That said, the model also has significant limitations. It does not assess political readiness, cultural fit, or administrative capacity. It does not prove that UBI caused the observed trends. And most importantly, it cannot substitute for human judgment, stakeholder input, or long-term field data.

In short, this project does not offer a verdict on whether UBI disincentivizes work—but it does offer a new way to ask smarter questions about where UBI might succeed next. By identifying where economic signals mirror those seen in successful trials, the model provides a bridge between high-level economic indicators and the grounded realities of poverty alleviation. In doing so, it offers a small but meaningful contribution toward a more equitable future—one where data can help open doors for those who have long been locked out of prosperity.

8. References (as Footnotes)

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