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WIP: Using Deep Learning to Analyze the Impact of Social Determinants on Mental Health Disparities in Urban vs. Rural Areas

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Leveraging Machine Learning to Uncover Mental Health Disparities Across Urban and Rural Communities: Insights from Social Determinants

Abstract

Mental health disparities between urban and rural areas are shaped by a complex interplay of social determinants, including socioeconomic status, access to healthcare, education, and community resources. Traditional approaches to understanding these disparities often rely on broad statistical models that overlook nuanced patterns in large datasets. To address this gap, we propose a machine learning-based framework to systematically analyze the impact of various social determinants on mental health outcomes in urban and rural communities. The proposed framework leverages balanced classification techniques, such as Balanced Random Forest (BRF), Gradient Boosting (GB), and eXtreme Gradient Boosting(XGB) classifiers to capture complex relationships between multiple social factors and mental health indicators. Using publicly available data from the Centers for Disease Control and Prevention (CDC), the model will integrate physical (e.g., level of exercise, BMI, and age), social (e.g., emotional support, childhood experiences, and personal experience of discrimination), and status (e.g., income, education, and employment) oriented characteristics to generate a comprehensive understanding of how social determinants impact mental health in diverse environments. By analyzing data from the view of population density, the model aims to identify specific factors that contribute to higher rates of depression, anxiety, and other mental health disorders in rural areas compared to urban settings. Through analyzing feature importance in the BRF classification model, we found that while the most impactful aspects of an individual's mental health was their physical characteristics and ability to function independently in both rural and urban environments. Additionally, the level of emotional support and loneliness these individuals experienced factors heavily into determining key mental health metrics. While in urban environments general health level played a more major role in determining mental health outcomes, in rural environments accessibility to and availability of food was an important feature that urban environments did not share. Our GB classification model reached an accuracy of 83.5% for depressive disorders, 66.5% for days of poor mental health, 49.5% for life satisfaction, and 73.0% for occasions of high stress across both urban and rural environments, demonstrating our model's flexibility in handling diverse data from different settings. The findings from this research can inform targeted public health interventions and resource allocation strategies to reduce disparities between rural and urban populations. Ultimately, this study highlights the potential of machine learning to provide a more granular understanding of mental health disparities and the role of social determinants. By uncovering hidden trends and complex interactions in large datasets, this research aims to guide policymakers and healthcare professionals in designing more effective, data-driven strategies for promoting mental health equity across both urban and rural settings.

1 Introduction

Mental health is an increasingly critical issue worldwide, affecting individuals across all demographics and geographies. According to the Substance Abuse and Mental Health Services Administration (SAMHSA), as many as 23.1% of adults in the United States experience mental health challenges annually, underscoring the urgency of addressing this growing public health crisis. Mental health outcomes are influenced by a multitude of factors, including socioeconomic conditions, environmental stressors, healthcare accessibility, and cultural norms. However, these factors vary significantly between urban and rural communities, leading to disparities in the prevalence, diagnosis, and treatment of mental health disorders [1-5].

Rural and urban environments often present contrasting stressors that can shape mental health outcomes in unique ways. In rural areas, limited access to healthcare services, social isolation, and economic challenges may exacerbate mental health issues. Conversely, urban areas may expose individuals to high population density, environmental pollution, and intense work-related stress, contributing to a different set of mental health concerns. These disparities are compounded by inequities in healthcare infrastructure, such as the uneven distribution of mental health professionals and resources, which further widen the gap in mental health outcomes between these populations [6-8].

Despite extensive research in mental health, most studies focus on specific populations, such as university students or clinical patients, often neglecting broader, population-level analyses. Furthermore, traditional methods heavily rely on statistical techniques that may oversimplify the complex interplay of social, environmental, and psychological factors contributing to mental health. This limitation highlights the need for advanced, data-driven methodologies that can uncover nuanced patterns and provide actionable insights for improving mental health outcomes.

In this study, we address these gaps by leveraging machine learning techniques to analyze and predict mental health metrics across urban and rural communities. By integrating structured data, such as socioeconomic indicators, with unstructured data, such as social media activity, our approach aims to capture the multifaceted nature of mental health determinants. This comprehensive analysis will not only provide a deeper understanding of the factors driving mental health disparities but also inform targeted interventions to reduce these inequities.

Our work is structured as follows: Section 2 discusses related works within the field and how we expand on this work. We then discuss our methodology in Section 3 which details our data collection, cleaning, and feature analysis before segueing into the construction of several classification models for mental health metric prediction. This will be followed by the evaluation of our models in Section 4 before we conclude our work in Section 5. We will then finish with our planned future work to improve our project in Section 6.

2 Related Works

Machine learning and its applications within the field of mental health is currently a popular topic in research, with many works revolving around integration into diagnosis frameworks [9]. Crisis intervention is a large part of the field as well, with recent work showing that machine learning has been valuable in clinical practice for caseload management and ameliorating risk [10]. Current work in the field of mental health with applied machine learning focuses mainly on prediction of specific illness with context drawn from individual patients' medical history or broad surveys. This has been accomplished with great success, resulting in many models with high accuracy being applied to illnesses ranging from schizophrenia to depressive disorders as explained in a comprehensive overview of mental health focused machine learning models [2]. A trend within these studies is to focus on specific groups such as college students at a university or patients within a hospital and have focused models that manage very specific target variables [3]. This exposes an opportunity for work to be done in broader examination of mental well-being that is not tied to explicit diagnosis. Many individuals in the country eschew medical intervention into personal mental difficulties, which can be navigated by examining data pertaining to broader aspects of mental well-being, such as stress level or satisfaction with life. These indicators may give a more accurate picture of general mental health within the country since many individuals may avoid formal diagnosis.

Studies that involve a broader examination of mental health trends across the nation tend to employ purely statistical methodology and neglect machine learning as a tool. A recent study employed nation-wide data on adverse childhood experiences and related it to mental well-being utilizing chi-square test, Pearson correlation, and linear regression [4]. Opportunity for advancement of the field exists in prediction models that can handle nation-wide datasets and draw broad predictions of mental well-being, taking the field a step further than purely statistical analysis. Another work involves analysis of environmental exposures and their interaction with mental health, which shows similar interest into how the environment can impact the psycological well-being of individuals [5]. This work, however, focuses on pollutants, climate change, and health promoting environments rather than the social and physical environments that we hope to explore within our own work.

Work that focuses on the impact of population density within the realm of mental health is sadly neglected, with a recent paper providing a call to action to fill the gap between rural and urban environments' responses to similar prevalence of mental illness [6]. They found that while the prevalence of mental illness is relatively the same between rural and urban environments, outcomes were drastically different, with adults receiving less care that is less effective. This highlights the need for further focus being provided to the disparities between rural and urban environments and how this impacts mental health outcomes in the populations of both.

Our work seeks to bridge the gap left by current research by providing a unique approach to mental health analysis, exploring broad, environmental data that focuses on disparities between rural and urban environments. Recent studies show that access to mental health services does not reflect the increased need for them, as 95.6% of adults report at least one barrier to accessing adequate mental health care, and 13.3% report no access to regular mental health services at all [8]. By exploring the root, environmental causes of poor mental health in communities of differing population densities, we can provide targeted information that can increase the efficacy of policy and intervention in unique demographics and improve access to mental health services.

3 Proposed Method

In this section we will discuss in detail our approach to data processing, evaluation, and model creation. We will begin with discussion of the cleaning and evaluation of public mental health data. This will segue into the description and comparison of several models classifying different aspects of mental wellness with respect to rural and urban well being.

3.1 Data Collection

This work was produced utilizing the Behavioral Risk Factor Surveillance System's (BRFSS) 2023 public dataset provided by the Centers for Disease Control and Prevention [7]. The BRFSS is a comprehensive survey touching on many different aspects of social wellness, personal habits, physical health indicators, and emotional well-being. An important aspect of this dataset is its anonymization, which removed many key indicators of personal data that could be used to track an individual's identity. This resulted in a dataset that cannot be traced back to any individual but still contains enough information to sort the data by rural and urban environments.

3.1.1 Data Cleaning

Since this data was sourced from a nationwide survey with a number of avenues of collection, thorough data cleaning was important to contextualize missing information, anomalous data entry, and entry patterns in the survey. Due to the focus of our work, we were able to disregard individuals that did not answer questions about the key mental health metrics that we would be tracking. From there, we focused on the individual variables that we determined provided a comprehensive view of an individual while still relating to our topic. After extensive review of the BRFSS codebook and analysis of individual variables and their context in relation with each other, much of the missing data was able to be implicitly coded as a represented value.

Many of the variables related closely to one another, with blocks of questions only being asked if the first question was answered affirmatively. This makes sense in context of the survey, since interviewers would not waste time entering data for questions that have no relevance to the individual. However, this resulted in a majority of the null entries within the dataset actually representing a negative value, or a ”no” in context of the survey. With this information, we were able to implicitly code null values following this pattern as a ”no” category. Some smaller cleaning work was performed as well, gathering ”Don't Know/Not Sure” and ”Refused” answers into the same category as well as blank entries if they did not follow the aforementioned pattern. Any leftover data entries with null values that were unable to be contextualized were dropped as a final step. In this way we were able to contextualize missing entries without losing the bulk of the meaning behind the data.

After cleaning, we split the data into two categories: individuals residing in rural counties and individuals residing in urban counties. From there, we separated out data points that represent whether an individual had ever been diagnosed with a depressive disorder, the number of days mental health has not been good in the past month, how satisfied they are with life, and how often an individual has experienced a high level of stress within the last month. These data points we set aside as the targets for our classification models, while all other variables were set aside as features in our model. This resulted in a dataset containing 205,503 samples with 117 different variables for each.

The most important observation made during this stage was the unbalanced nature of our data. Many respondents of the survey reported positive values of mental, physical, and social aspects of health, which skews our data towards primarily healthy individuals.

3.1.2 Feature Analysis

Before constructing models and comparing their functionality, we first performed some analysis of feature importance utilizing a *BalancedRandomForestClassifier*. This model was chosen due to its ability to handle unbalanced data and its functionality in allowing us to analyze the relationships between features and targets. Since there are many variables available to us, we wanted to limit our focus to only the most relevant, since too many variables could result in overly complex and computationally costly models that could overfit. In Figure 1 we display the top twenty features across all targets in order of importance for urban counties, and in Figure 2 we display the same for rural counties. With these variables flagged for importance, we will be able to tailor our models to take into account only these twenty features instead of the entire dataset.

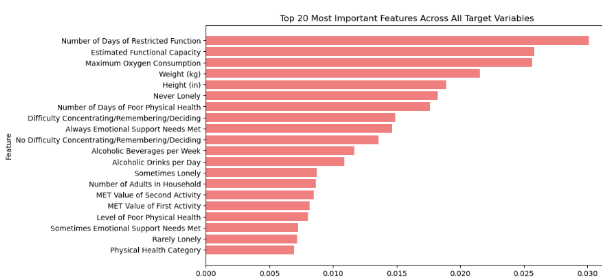

Figure 1: Feature importance across all target variables for urban counties.

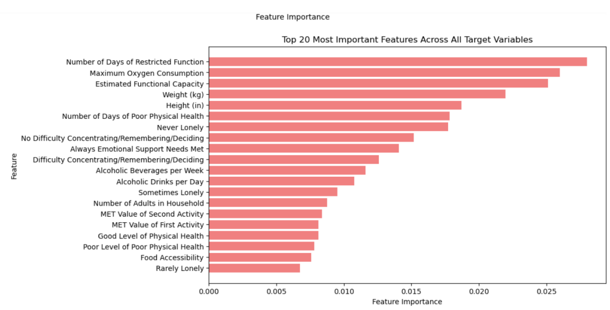

Figure 2: Feature importance across all target variables for rural counties.

While features are relatively the same across both rural and urban models, there are some interesting differences in the lower importance variables. In rural counties, level of physical health and food accessibility are more relevant metrics, but in urban counties the degree of which an individual's emotional support needs being met factors more heavily into consideration. For both areas, the main variables that affect mental health the most involve the functionality of the individual, or their ability to function independently, and general health metrics such as weight, height, and oxygen consumption.

3.2 Model Structures

In order to determine efficacy of machine learning prediction of key mental health metrics across urban and rural environments, we constructed several models focusing on multi-output structures that are able to adapt to unbalanced data. We chose to compare the *BalancedRandomForestClassifier*, *AdaBoostClassifer*, *XGBClassifier*, and *GradientBoostingClassifier*. This is due to their adaptability to a multi-output structure that can classify both binary and multi-class targets with unbalanced features.

In Tables 1, 2, 3, and 4 we list the hyperparameters of each model, found by utilizing a *RandomizedSearchCV* which compared random combinations of various hyperparameters in order to find the optimal accuracy for each model.

Hyperparameter	**Value Chosen**
N Estimators	100
Max Depth	None
Min Samples Split	5
Min Samples Leaf	1
Max Features	sqrt
Bootstrap	False

Table 1: Balanced Random Forest Structure

Hyperparameter	**Value Chosen**
N Estimators	50
Learning Rate	1.0
Max Depth	3
Base Estimator	Decision Tree Classifier

Table 2: AdaBoost Structure

Hyperparameter	**Value Chosen**
N Estimators	100
Max Depth	None
Min Samples Split	5
Min Samples Leaf	1
Max Features	sqrt
Bootstrap	False

Table 3: XGBoost Structure

Hyperparameter	**Value Chosen**
N Estimator	100
Learning Rate	0.1
Max Depth	3
Min Samples Split	2
Min Samples Leaf	1

Table 4: Gradient Boosting Structure

4 Evaluation

Throughout this section, we evaluate the performance of each model for rural and urban mental health prediction. We examined the accuracy, precision, recall, and F1 Score of each model in order to determine the most optimal model for each case. Figure 3 and 4 display the average accuracy of each model's performance across every output for urban and rural areas respectively.

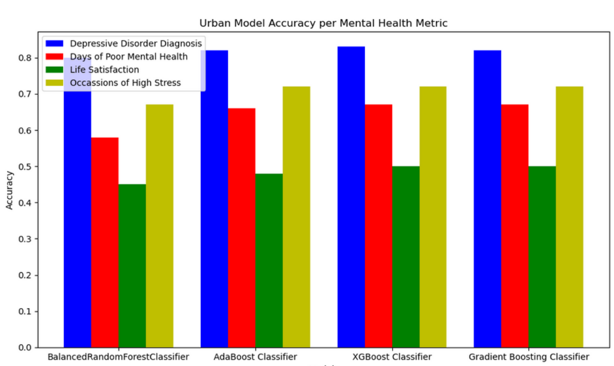

Figure 3: Accuracy of each model per output for urban counties.

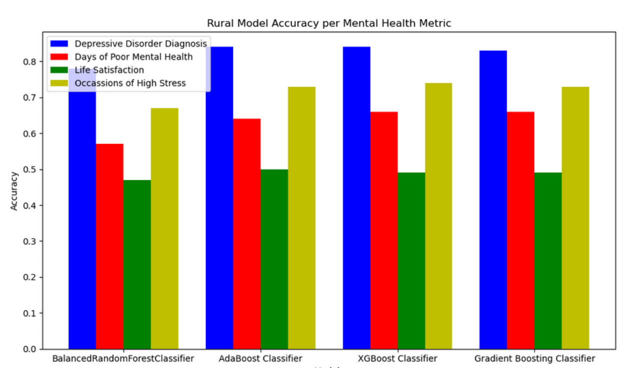

Figure 4: Accuracy of each model per output for rural counties.

The models across the board performed well for classifying depressive disorders in individuals and relatively well for occasions of high stress and days of poor mental health. The lowest accuracy achieved by the models belonged the variable of life satisfaction. Gradient Boosting Classifier achieved the highest accuracy for each model in both urban and rural contexts, achieving an average of 0.835 for depressive disorders (DDD), 0.665 for days of poor mental health (DPM), 0.495 for life satisfaction (LS), and 0.73 for occasions of high stress (OHS).

In Tables 5, 6, 7, and 8 we record the weighted average of the precision, recall, and F1 score of each target variable for each model across rural and urban counties. The weighted average accounts for the unbalanced nature of the data and compensates for underrepresented target classes.

	Urban			Rural		
Target	**Precision**	**Recall**	**F1 Score**	**Precision**	**Recall**	**F1 Score**
DDD	0.80	0.77	0.78	0.81	0.78	0.79
DPM	0.65	0.58	0.60	0.63	0.57	0.59
LS	0.47	0.45	0.46	0.48	0.47	0.47
OHS	0.69	0.67	0.68	0.71	0.67	0.69

Table 5: Balanced Random Forest Classifier Weighted Average Metrics per Target

	Urban			Rural		
Target	**Precision**	**Recall**	**F1 Score**	**Precision**	**Recall**	**F1 Score**
DDD	0.80	0.82	0.80	0.82	0.84	0.81
DPM	0.65	0.66	0.65	0.63	0.64	0.63
LS	0.47	0.48	0.47	0.47	0.50	0.48
OHS	0.70	0.72	0.69	0.70	0.73	0.71

Table 6: AdaBoost Classifier Weighted Average Metrics per Target

	Urban			Rural		
Target	**Precision**	**Recall**	**F1 Score**	**Precision**	**Recall**	**F1 Score**
DDD	0.81	0.83	0.80	0.82	0.84	0.82
DPM	0.66	0.67	0.66	0.65	0.66	0.66
LS	0.48	0.50	0.48	0.47	0.49	0.47
OHS	0.71	0.72	0.70	0.71	0.74	0.72

Table 7: Gradient Booster Classifier Weighted Average Metrics per Output

While each model had relatively similar performance, the Gradient Booster Classifier had a slight edge on the others. From all metrics discussed in this section, we can see that all models perform equitably for both rural and urban counties. This is significant, as the rural data recorded had drastically less samples than urban counties, which meant that an already unbalanced dataset was worse for rural models. This shows that our models perform equally for underrepresented geographical locations as their counterparts.

	Urban			Rural		
Target	**Precision**	**Recall**	**F1 Score**	**Precision**	**Recall**	**F1 Score**
DDD	0.80	0.82	0.80	0.80	0.83	0.81
DPM	0.66	0.67	0.66	0.65	0.66	0.65
LS	0.48	0.50	0.48	0.47	0.49	0.47
OHS	0.70	0.72	0.70	0.71	0.73	0.71

Table 8: XGBoost Classifier Weighted Average Metrics per Output

5 Conclusion

This work presents a targeted approach to mental health prediction and evaluation that acknowledges the differences in rural and urban environments and how they effect mental well-being. By extracting the importance of features dependent on population density we were able to see that many important features are shared, such as ability to function, loneliness, physical health metrics, and alcohol consumption. The fact that the top five important features for both models are the same and involve mostly physical characteristics and ability suggests a strong correlation between the physical wellness of an individual and their emotional state. This does not discount, however, the importance of social needs to an individual, such as emotional support from their community and relative loneliness which feature as relatively high importance for both models. A stand out metric in rural prediction models was food accessibility, which brings about a broader question on how infrastructural differences between rural and urban communities could shape mental health outcomes.

We found through our evaluation of various models, that it is possible to reach relatively high accuracy and precision for specific mental health metrics, such as depressive diagnosis, prevalence of high stress, and days spent with poor mental well-being, but is slightly lacking when it comes to more general statistics, such as life satisfaction. Our Gradient Boosting Classifier ended up providing the highest accuracy metrics, achieving an average of 0.835 for depressive disorders, 0.665 for days of poor mental health, 0.495 for life satisfaction, and 0.73 for occasions of high stress across rural and urban environments. With such equivalent results between rural and urban environments, we can confidently say that our models perform equally well when taking population density into context.

With these models and feature analysis, we hope to push mental health tracking in the country towards a more equitable approach, taking into account nuances of the environment individuals reside in. Important aspects of the population's well-being can be neglected if considered from a solely broad perspective, and attention must be paid to the differences in lifestyles that environments can influence.

6 Future Work

Due to anonymization of datasets, it is difficult to connect different sources of data utilizing key identifiers such as census tract numbers. This limited our scope to an individual dataset and what information it could provide. In future work, we hope to reach out to different institutions to request access to data that has limited identifying information attached to it so that we can incorporate a broader perspective of the differences in rural and urban environments. This would be limited to census tract level data so as to not totally deanonymize sensitive information and would allow us to analyze the impact of community wellness, public infrastructure, crime, and other environment-specific information on the mental well-being of individuals residing in those areas as well as incorporate unstructured data from social media. With a broader perspective, we hope to gather more insight into the unique needs of individuals' mental wellness and improve the accuracy of our models to achieve accurate tracking of mental metrics across the country.

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