AI's Racism: How Racially Biased Data Affect Machine Learning

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I. INTRODUCTION

The advancement of computer technology has enabled the development of artificial intelligence, which has begun to contribute to the medical field for health and life, which are human aspirations. Artificial intelligence in this context can be defined as the computational understanding of what is commonly referred to as intelligent behavior and the creation of artifacts that exhibit such behavior [1]. There have been steady and dramatic advances in the use of artificial intelligence systems to diagnose patients. AI can learn from audio and visual data to identify new types of diseases or patterns, provide personalized treatment options, or help track infectious diseases and prevent their spread [2]. Because AI is better than humans at analyzing patterns and learning from large amounts of data, it is expected to replace traditional clinicians to provide better healthcare for all humans.

The medical field has contributed to health improvements over the past 50 years, as evidenced by increased life expectancy and decreased mortality rates for all races [3], but it has not been free of racism. Racism in the medical field includes individual discrimination by healthcare providers. Still, it is also driven by institutional discrimination, including geographic disparities in healthcare resources, patient preferences, economic status, differences in insurance coverage, trust in medical procedures, and medical knowledge and familiarity with race [4]. While this institutional racism may be partially addressed by AI acts in the medical field, AI may face new forms of racism.

As AI supports healthcare in a variety of ways, the racism that can occur and the problems it can cause are varied and, in some cases, severe. Since AI challenges and strengthens areas that humans have not been able to do based on existing data, if AI is used continuously without solving the problem of racism, the problem of racism will become more serious and create more discrimination and gaps in the medical field as technology advances. This study seeks to understand how racial bias is instilled and how racism occurs in the various ways that AI assists in healthcare and to create a data model to directly address the severity of racism in AI and how it can be improved.

II. BACKGROUND

A. *Artificial Intelligence*

Artificial Intelligence is primarily concerned with understanding and performing intelligent tasks such as reasoning, learning new skills, and adapting to new situations and challenges. The concept of AI itself is very abstract and can be categorized into analytical AI, functional AI, conversational AI, textual AI, visual AI, and more [5].

B. *Machine Learning*

Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) are three words often used to describe software that can think and make decisions on its own. Among machines and systems that think with general human-level intelligence, the process of analyzing and making decisions based on data accumulated through experience is referred to as machine learning, and within this is deep learning, which operates through multiple neural networks [5].

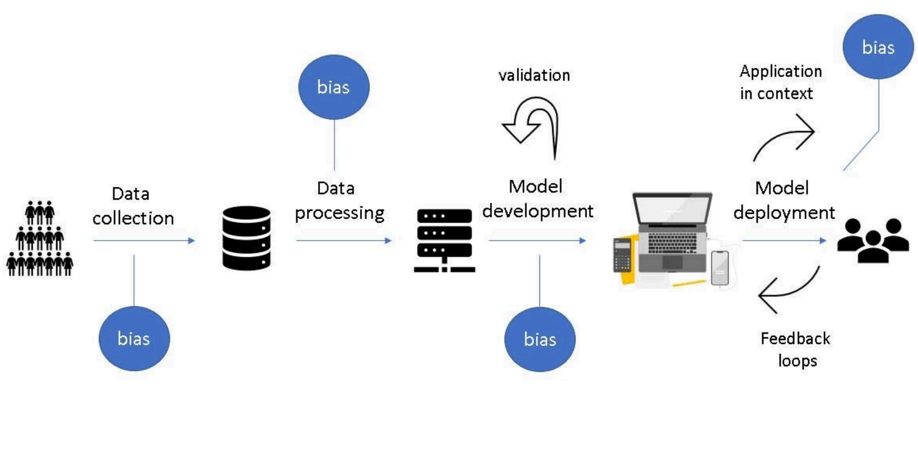

Fig. 1. Stages in which bias intervenes.

C. *Bias in Datasets*

Bias in machine learning can occur at any stage of the process, including data collection, algorithm design, and model application [6]. Using medical data as an example, bias in machine learning can occur when data is collected that is already racially biased when it is processed without removing racial bias, when a model is developed that is biased against a particular race, and when the model is applied that is biased against a particular race.

III. LITERATURE REVIEW

A. *Impacts of Bias*

Many medical institutions, research institutes, and human rights organizations are constantly thinking about how racism from artificial intelligence bias will affect healthcare provision. Their fundamental goal is to provide equal healthcare to all regardless of race and gender, so they are offering solutions to AI with some examples of how bias works. Jindal from Brown University Hospital expressed concern about racism in artificial intelligence by focusing on the steps that bias becomes operational [7].

The vast amount of raw data used in machine learning can be biased to represent the entire minority group during data collection, express preference for a particular race, and racial discrimination can occur in health information exchange used in healthcare [7]. The most representative example is the bias in the data from the vaccination rate during the coronavirus. To evaluate the stability against the mRNA-1273 vaccine, 30,351 vaccinated persons were recruited, of which the proportion of white/other races was 79.2/20.9\%. In severe cases, the sample even widened to 98/2\% [8]. In this case, it can be seen that the effectiveness on white people will be well proven, but for other races, or even races where no samples have been collected, it will be difficult for that race to expect a proper outcome.

Using natural language processing as an example, he suggested that human labeling can cause bias in the data processing stage [7]. Labeling cannot be completely fair, so human biases are bound to enter, for example, labeling certain races as offensive to verbal aggression but "toughness" to justify violence against others. In addition to NLP, such examples can be found in various fields of AI. In the case of facial recognition, white men's faces label and process the main dataset as human, so it is highly likely that non-white or non-white people will not be recognized as human [9].

When it comes to developing models after preparing data, bias is primarily used in determining parameters, feature selection, and performance metrics that model developers manually adjust. Jindal emphasized the need for careful attention at this stage because it is difficult to know or monitor whether racism will occur if the public or healthcare workers other than model developers do not have knowledge and interest in it [7]. Close cooperation between engineers and medical personnel is required at this stage, but if parameter settings are arbitrarily set on one side, objective indicators cannot be received. The parameters of a particular race can be applied to other races as a representative, or the parameters can be set through speculation without strong external verification.

The final step in which bias can work is the implementation of artificial intelligence models. Using a model developed to include some or all of the above-mentioned biases will naturally lead to racial discrimination, which is already low in accuracy or racial bias in various models such as population health, kidney function discrimination, voice recognition, and dermatological photo scanning [7]. However, even the perfect model, applying the AI model to a specific race can also act as a bias. If the artificial intelligence model is applied only to a specific race in the procedure of clinical treatment, both the opinion of the doctor and the opinion of the artificial intelligence are included in the final diagnosis, so they do not receive the same results as other races, positively or negatively.

B. *Mitigating Bias*

Solving overall racism by resolving the interventions of these biases is not simple. Even if race is simply deleted among features, there may be variables deeply related to race or racial data that are not visible throughout the data, so it ignores the problem and does not solve it [7]. Nevertheless, mitigating bias in AI, especially in the medical field, is a critical area of research that aims to ensure fair, accurate, and equitable outcomes in healthcare applications.

The most fundamental and simplest solution is to have an equal number of datasets for all races and to proceed the machine learning. In the case of the COVID-19 vaccination rate mentioned above, all datasets were concentrated only on white people, so the model can recruit the same number of races to find out the overall efficacy, or it can find out the independent efficacy on a racial basis.

In addition, rather than simply using raw data, synthesizing and using various and fair features together helps to eliminate bias. For example, when studying models used to diagnose skin cancer, it was found that images of dark-skinned people were lacking a lot, which in conclusion could lead to serious medical losses such as unnecessary surgery and missing treatable cancers. Thus, the researchers used quality diversity algorithms to synthesize and test up to four diversity metrics in the dataset: skin color, gender, age, and hair length, which increased accuracy for faces with dark skin color and resulted in maintaining training accuracy for additional data [11].

This diversity improvement is not just necessary for datasets. Reducing minority under-representation goes beyond collecting data from existing standards of majorities, working with data/artificial intelligence organizations that represent minorities, such as Black in AI, Data for Black Lives, and the Algorithmic Justice League, can aim for diversity and eliminate bias in the data collection stage itself [12]. Lowering the barriers to testing themselves by considering socioeconomic factors, or using fairer and more accurate algorithms rather than intentional bias algorithms, will also greatly contribute to the improvement of the overall process.

III. THEORETICAL FRAMEWORK

In the medical field, many studies and modeling are being conducted to avoid bias and eliminate AI racism. Based on the COVID-19 data labeled with race and the key points of the literature review mentioned above, this study attempts to find out how racial factors affect the outcome of machine learning and how it can be improved. Two models are created in this study, and the first is a model that uses machine learning to determine how much race itself has a significant impact on a dataset, which performs a model-based feature importance through random forest. Another model uses a support vector machine to create a program similar to a patient screening program used in the actual medical community to determine how race affects patients.

A. *Feature Importance Model*

The feature importance model is a model to find out how much race contributed to death when the coronavirus made a person fatal. It is possible to find out which race was more vulnerable to the same virus, or whether socioeconomic factors had a greater impact. Feature importance is mainly used during the feature selection process that makes data sets such as feature selection easy for machine learning, and this is a process that allows you to find out how much various features contribute to one feature, for this model, death [13].

Random forest was used as a learning method to perform the feature importance. Random forest works by constructing a multitude of decision trees during training and the result is derived from how often a feature is used to split a node across all trees and how significant the split is towards reducing impurity [14]. Random Forest is particularly useful for feature importance because it provides a straightforward metric to measure the importance of each feature: the decrease in node impurity weighted by the probability of reaching that node. In simpler terms, features that more frequently split nodes effectively (reducing uncertainty in the outcome) across many trees are deemed more important [15]. The importance of each feature in the Random Forest model gives a clear indication of how each feature contributes to the accuracy of the model.

B. *Patient Classification Model*

Patient classification models are models that can be used in the medical field to create a demo of a model that shows how much this is affected by Racism in AI. One of the supervised learning methods, the Support Vector Machine (SVM) method, is one of the methods in the medical community to classify and organize groups through a classification algorithm [16]. This model can be used as a model to help patients diagnose their risk and determine whether they should be treated selectively.

Support Vector Machine is a powerful, supervised machine learning algorithm used for both classification and regression tasks, but it is more commonly used in classification problems. SVM works by finding the hyperplane that best divides a dataset into classes. The strength of SVM lies in its ability to handle high-dimensional data and its effectiveness in cases where the number of dimensions exceeds the number of samples [17]. SVM constructs a hyperplane in multidimensional space to separate different classes. The best hyperplane for an SVM is the one with the largest margin between the two classes. Margin is a gap that no instances are in on either side. The larger the margin, the lower the generalization error of the classifier. SVM supports both linear and non-linear classifications using what's called the kernel trick. The kernel trick involves transforming data into a higher dimension where a hyperplane can be used to separate data into different classes [18].

V. METHODOLOGY - FEATURE IMPORTANCE

A. *Model Description*

Among the many factors that influenced the risk of the coronavirus, the model was designed to determine how much race itself contributed to death. For example, some races were resistant to the virus, and it may have been their geographical conditions that led to their infections and deaths, while others lived in geographically safe places, but those races themselves were susceptible to the coronavirus and could have been considered infected and died. The goal of the model is as follows.

- Race would not have had much of an impact on the coronavirus - which was considered the biggest goal because traditional statistical models or biased AI might have evaluated the death of a particular race without socioeconomic factors.
- If it's not race, the age group and the education level will have the biggest impact.
- The cause of infection/death for people living in cities is that the geographical component of their place of residence is greater than race.

B. *Data Acquisition*

Since COVID-19 was a global disease that occurred after the concept of machine learning was introduced and fully commercialized, a large amount of data has been recorded and published, but in this research to solve racial bias, realistic and reliable data was the key to producing reliable results. Therefore, a dataset provided by the National Center for Health Statistics, officially registered with the Centers for Disease Control and Prevention, was used [19], [20], of which the data provided by The Bureau of Economic Analysis was used to determine the income level of the county [21].

C. *Data Pre-Processing*

The dataset from the first of the Feature importance models contained data [19] on all deaths from 2019 to 2020, of which data from 2019 and those who had causes of death unrelated to COVID-19 among the 2020 deaths were excluded because the analysis was unnecessary. Data with unknown races were also excluded because unknown races would confuse the results. Since the date of completion of data collection was written in the first column unnecessarily, the column was excluded, and total deaths were also excluded because they contained unnecessary data other than those who died from COVID-19.

The data set of the second model[20] also included deaths from all causes, and data from the entire county population were included, so all of them were excluded. In addition, columns on the start and end dates of data collection, which are unnecessary columns, were excluded. In the data, all of the data marked empty spaces, that is, null, referred to as 0, so they were filled with zero. In addition, since the income for each county announced by BEA[21] was influenced by COVID-19 from 2020 to 2022, a new column called Income per Capita was created by averaging them for smoother learning.

D. *Feature Selection*

The first model was to find the factor that contributed the most to the death from the coronavirus, so the deaths were targeted. In addition, the features that contributed to the death were set at the education level, race or Hispanic origin, sex, and age group. Among them, the education level was set to know the socioeconomic status of the deceased because educational achievement is frequently and reliably used as a more reliable measure of socioeconomic status than occupation or income [22].

In the second model, because the features of coronavirus death by county were to be identified, the number of deaths was used as a target feature, races, urban description, and home per capita as contributing features. The educational level was not available in this model, where each row was a statistic combining the number of deaths in the county rather than representing one person, making the county's overall Income per capita one of the socioeconomic factors.

E. *Experimental Setup*

1) Configuration: The experimental setup for this study utilizes the Python programming environment, leveraging libraries such as Pandas for data manipulation, Matplotlib, and Seaborn for visualization, and Scikit-learn for machine learning tasks. The software version specifics include Python 3.8, Pandas 1.2, Scikit-learn 0.24, and Matplotlib 3.3.4. The computational experiments were conducted on an Apple MacBook Pro equipped with an M2 Pro chip and 16GB RAM, ensuring adequate processing power for the machine learning computations.
2) Parameters: The Random Forest Regressor was configured with 100 trees (`n_estimators=100`), which provides a balance between computational efficiency and model performance. Other parameters include a default `max_depth` to allow the trees to expand until all leaves are pure or until all leaves contain less than

`min_samples_split` samples, set to 2. The model uses a `random_state` of 42 for reproducibility of results.

VI. RESULTS - FEATURE IMPORTANCE

A. *Feature Importance Analysis of Model 1*

The results of the model were derived similarly to expected. It was found that the age group had the greatest influence on the mortality rate of the coronavirus, and the education level was found to have an unexpectedly lower influence than race. This raises concerns about potential data bias if these features correlate with socioeconomic or health-access disparities.

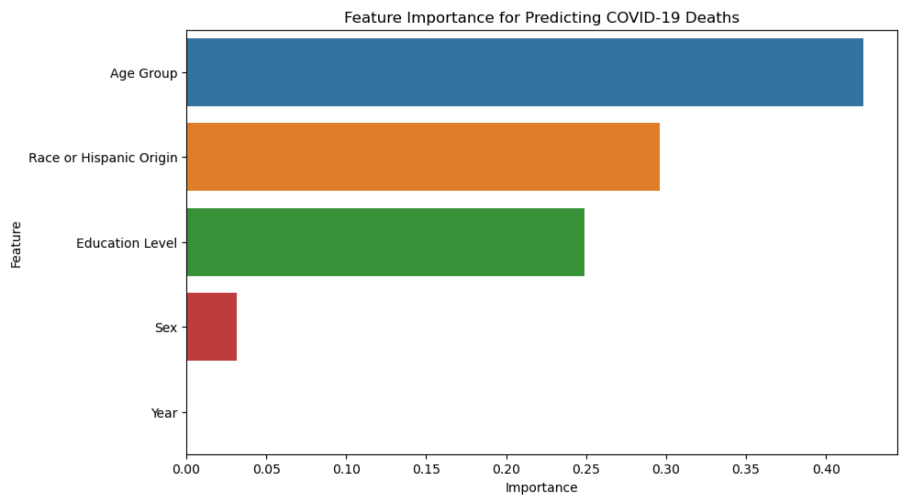

Fig. 2. Result of Feature Importance Model 1.

B. *Evaluation of Metrics of Model 1*

1) Primary Metrics: The model's performance was evaluated using regression-specific metrics due to the continuous nature of the target variable (COVID-19 deaths). These included:

- Mean Absolute Error (MAE) - 221.3149: This metric tells that, on average, the predictions of the model are about 221.31 units off the actual data points. The unit here would be the number of deaths, which means each prediction deviates from the actual value by this amount on average.
- Mean Squared Error (MSE) - 212519.8966: The MSE is significantly higher because it squares the errors before averaging, thus giving a heavier penalty to larger errors. This

number suggests there are variations in the error size, with some predictions being much farther from the actual values than others. Like MAE, the acceptability of this value depends on the scale of the death counts.

- R-squared (Coefficient of Determination) - 0.9178: An R-squared value of 0.9178 indicates that approximately 91.78% of the variance in the dependent variable (COVID-19 deaths) is predictable from the independent variables (Education Level, Race or Hispanic Origin, Sex, Age Group). This high value suggests that the model explains a significant portion of the variability in the outcome, indicating strong predictive power.

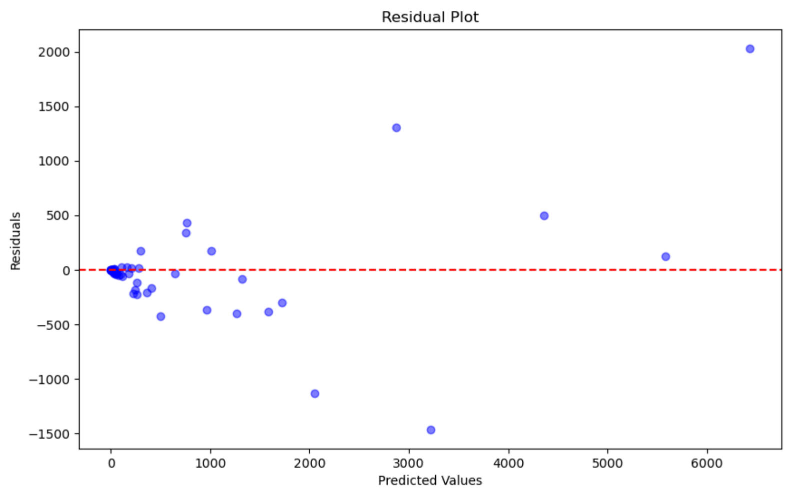

Fig. 3. Bias Detection Metrics Residual Plot of Model 1.

- Bias Detection Metrics - Residual Plot: The residual plot suggests that while the model performs reasonably well for many observations, there are certain areas, especially at higher levels of predicted deaths, where the model's predictions could be improved. Investigating the characteristics of these outliers could provide valuable insights into further model refinement.

C. *Feature Importance Analysis of Model 2*

In the model's results, the county where the deceased lived was the large central metro, and other factors such as non-Hispanic Asians had a significant impact. This indicates that the more downtown the county, the more COVID virus spreads to people and leads to death, as predicted, but can recognize that the data has become biased because it also indicates that Asian or Hispanic people died for racial and ethnic reasons.

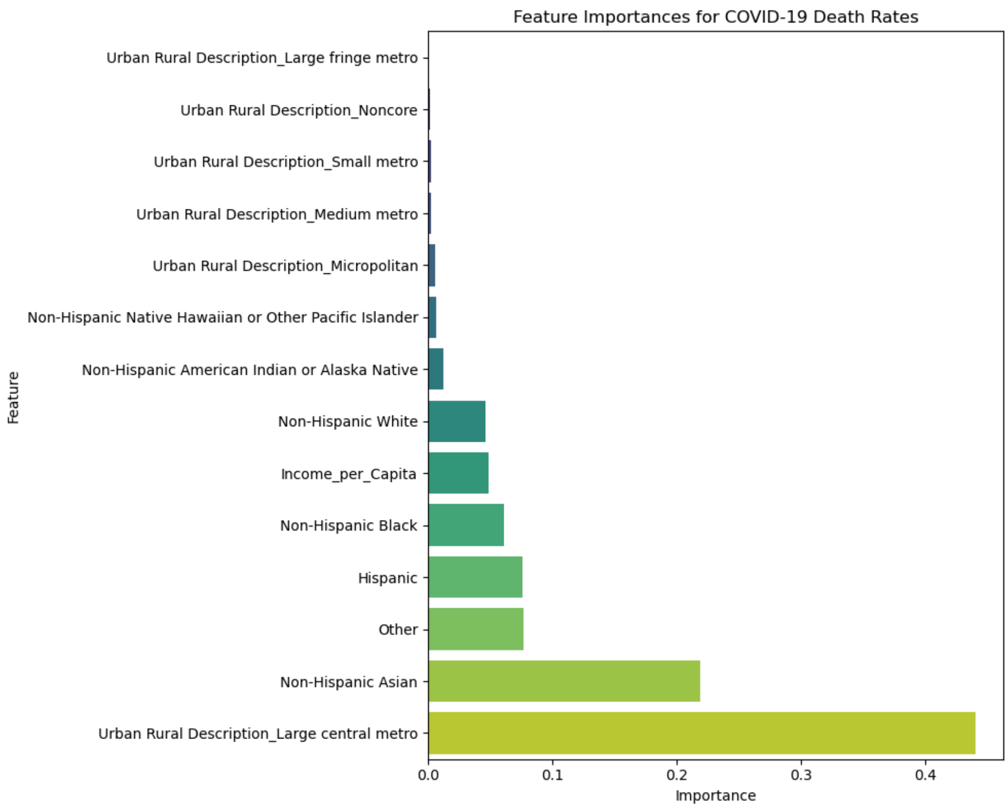

Fig. 4. Result of Feature Importance Model 1.

D. *Evaluation Metrics of Model 2*

1) Primary Metrics: The model's performance was evaluated with the same metrics as Model 1.

- Mean Absolute Error (MAE) - 4545.968232758621: The MAE being 4545.968 is quite high, indicating that on average, the model's predictions deviate from the actual death counts by approximately 4545.968 deaths. This high error suggests that the model may not be capturing all the nuances of the dataset, potentially missing key predictors or interactions between features that are influential in determining COVID-19 death outcomes.
- Mean Squared Error: 331536286.3796987: The MSE is extremely large, further emphasizing that there are large errors in some predictions. MSE is particularly sensitive to outliers because it squares the prediction errors. The substantial value here could be

indicating the presence of outliers in the data or instances where the model is particularly inaccurate.

- R-squared: 0.5064753697984699: An R-squared of approximately 0.51 means that about 51% of the variance in the observed death counts can be explained by the model's inputs. While this is a moderate figure, it also implies that nearly half of the variability in death outcomes is not captured by the model. This could be due to missing important predictors, inadequate model complexity to capture the relationships in the data, or substantial noise in the dataset.

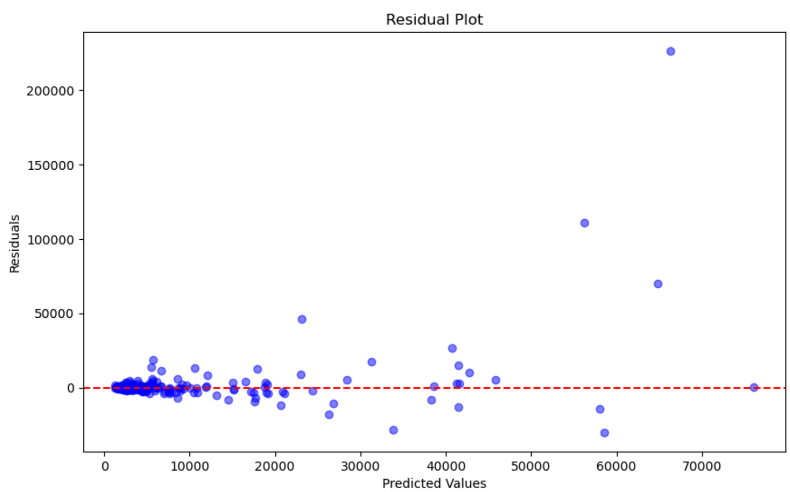

Fig. 5. Bias Detection Metrics Residual Plot of Model 2.

- Bias Detection Metrics - Residual Plot: The plot shows that for a large portion of the data, particularly for lower predicted death counts, the residuals cluster around the zero line. This indicates that the model is capable of accurately predicting COVID-19 death counts when the numbers are relatively low. As the predicted death counts increase, the residuals also become larger and more dispersed. This trend is particularly noticeable with a few data points exhibiting significantly high residuals. These instances suggest that the model's predictive accuracy diminishes as the number of deaths increases, which could be due to model limitations in handling higher ranges of data or a lack of representative training data for these scenarios.

VII. METHODOLOGY - PATIENT CLASSIFICATION MODEL

A. *Model Description*

The model utilizes a Support Vector Machine (SVM) to assess the risk associated with COVID-19 based on various demographic factors such as race/ethnicity, age group, and sex. This approach is chosen to capture the nuanced effects of these variables on COVID-19 outcomes, which may not be linear. The primary goal of this model is to understand how different demographic factors contribute to the risk of COVID-19 mortality and to identify high-risk groups, thereby helping in targeted public health responses and interventions. In addition, the expectation for the results of the model is that the results of racial division will produce different results than those of non-racial division.

B. *Data Acquisition*

The dataset used in this model was provided by the National Center for Health Statistics and registered in the Centers for Disease Control and Prevention, the same dataset used in the feature importance model [23].

C. *Data Preprocessing*

The dataset was meticulously cleaned to ensure the accuracy of the analysis. Data for 2019, the year of death of the deceased was excluded, and columns corresponding to the date of analysis, year, and month were excluded. Because of COVID, the ward is complex and the model is used when patients are selectively classified and received, excluding years when the coronavirus was not threatening. In addition, those who died from COVID-19 alone and those who died from COVID-19 and other complications were all treated as COVID-19-induced deaths to ensure the treatment of COVID-19 patients.

D. *Feature Selection*

Features selected for the model include demographic features and racial indicators. There are demographic features of age grouped in 10-year increments and gender, and racial indicators.

E. *Experimental Setup*

1) Configuration Setup: The same configuration setup used in the feature importance above is used. In addition, The SVM was configured with a linear kernel to facilitate the interpretation of the impact of each feature. The model was trained on a split of 70% training data and 30% testing data, ensuring a robust assessment of its predictive power.
2) Parameters: The SVM model was configured with a linear kernel to ensure interpretability, a regularization parameter C optimized through cross-validation for

balance between complexity and performance, and a random state set to 42 for result reproducibility.

VIII. RESULTS - PATIENT CLASSIFICATION MODEL

A. *Comparison and analysis of the Model*

As expected, the model classified older patients as high-risk groups for COVID-19, and this resulted in the same result even if race was included as a feature. On the other hand, gender did not significantly affect the classification of high-risk groups. This is a situation that fits well with the results of the feature importance shown above. In addition, also as expected, since non-Hispanic whites were classified as relatively low-risk groups for all ages in the model, there may be situations in which they are filtered out of selective treatment and cannot receive treatment.

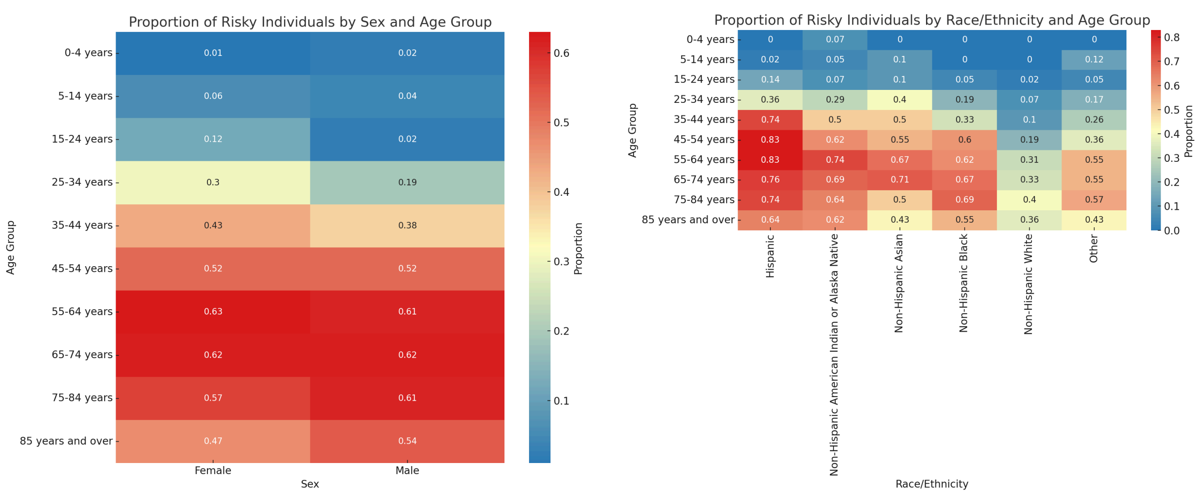

Fig. 6. Classification model without and with the race indicator.

B. *Evaluation Metrics of the Model*

This model is designed to evaluate accuracy based on the total number of predictions and correct predictions. The accuracy value of this model is 0.75, and it can be said that 75% of the predictions were accurate. However, since the value of this accuracy requires other benchmarking, this accuracy cannot be judged that the model was successful at this point.

IX. CONCLUSION AND FUTURE SCOPE

The study investigated the racial bias of artificial intelligence in healthcare and its impact. The models used feature importance and patient classification models to identify what factors racial bias plays in COVID-19 patients' mortality and found that race and socioeconomic factors also play an important role. The findings highlight the need for data diversity and multifaceted analysis approaches in machine learning used in healthcare. The patient classification model achieved an accuracy of 75%, indicating a significant but incomplete ability to predict risk across different groups accurately. It highlights the need for continuous improvement to ensure that AI models are effective and equitable. In addition, a better patient classification model can be developed with this 75% indicator. At this time, it remains a challenge to research and develop socioeconomic factors in addition to race and gender to enable selective management through more detailed patient surveys.

In addition, the second model of Feature importance showed a lot of improvements. MAE and MSE have confirmed that there are many errors, which need to further break down additional data or socioeconomic factors to add meaningful features. Also, because it has a low R-squared value, this could indicate model underfitting, where the model is too simple to capture the complex relationships in the data, or it might suggest that key predictive features are missing. In addition, the goal of the next research is to catch outliers through improved preprocessing and improve the complexity of the model to further repair and develop the model.

To prevent the continuation of existing gaps in the future, it is important to include ethical considerations in AI development. Collaborative efforts among data scientists, medical experts, and ethicists are essential to ensure that AI tools are served fairly in all communities. Responsible use of AI remains a challenge while strengthening medical delivery and preventing prejudices that may damage the vulnerable. AI offers important potential to change healthcare, but its application must be handled carefully to promote justice and equity in medical outcomes.

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