IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)
An International Open Access, Peer-reviewed, Refereed Journal

PREDICTING MEASURES TO OVERCOME THE MENTAL INSECURITIES IN WOMEN USING MACHINE LEARNING MODELS

[1]J Rosary Nancy, [2]P Sneka, [3]Dr. P. Meenakshi Sundari
[1]Post Graduate Student, [2]Post Graduate Student, [3]Assistant Professor
[1]Department of Computer Science,
[1]Fatima College, Madurai, India

***Abstract*:** This research paper delves into the application of the Python programming language for analysing and addressing women's insecurities. It explores the methodologies employed to comprehend and mitigate these insecurities across different life domains, while also acknowledging the constraints of these approaches. The paper investigates the diverse range of features and functionalities within Python that make it suitable for analysing data pertaining to women's insecurities. Additionally, it scrutinizes the characteristics of these insecurities, including their prevalence, root causes, and impacts, illustrating how Python can offer valuable insights into these intricate issues. Furthermore, the paper examines various Python packages and libraries such as NumPy, Pandas, and Matplotlib, commonly utilized for analysing data relevant to women's insecurities. It also delves into the multifaceted aspects of women's insecurities, spanning skill development, employment prospects, gender biases, financial worries, and societal expectation.

***Keyword* -** women insecurities; societal expectation; skill enhancement; finance; gender discrimination.

I. INTRODUCTION

Insecurity often stems from a lack of confidence and vulnerability, affecting various aspects of life. The goal is to uncover the triggers behind these insecurities. According to research conducted by The Wealthier Network, a think tank, 79 percent of women admitted to grappling with their self-esteem due to these underlying factors, with a focus on understanding the root causes of women's insecurity. Young women frequently encounter discomfort and limitations in mobility, leading them to assume sole responsibility for their safety. In psychology, insecurity manifests as an emotional response to perceived threats or dangers, with its effects extending beyond the individual woman to impact her social circle. Major factors contributing to women's insecurities in society include low self-esteem, past trauma and abuse, perfectionism, recent setbacks, excessive social media use, frequent criticism, and fear of failure.

This project aims to analyse these issues using machine learning, a critical tool in various fields. In the realm of artificial intelligence, machine learning involves creating algorithms and models that learn from data to make predictions. By recognizing patterns and generating precise predictions, machine learning can guide decision-making in uncertain situations. Exploratory Data Analysis (EDA) is employed in machine learning to preprocess data by addressing missing values, outliers, and feature scaling. The project focuses on identifying significant factors contributing to women's insecurities and providing suggestions to overcome these challenges.

II. METHODOLOGIES

Machine learning modules are software libraries offering pre-built tools, algorithms, and functions for streamlined development of machine learning models. They empower developers and data scientists to utilize existing implementations, minimizing manual coding, and facilitating the application of machine learning techniques across diverse domains.

The key components of Machine Learning Models are:

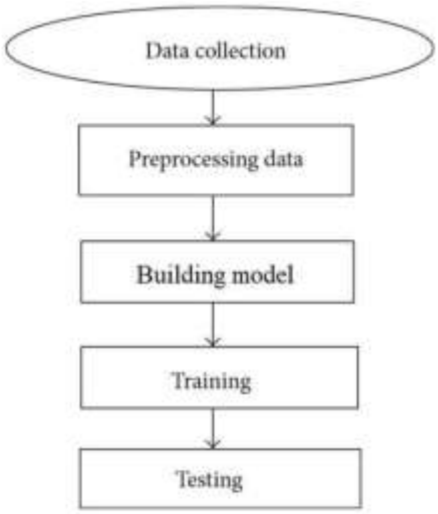
- Input Data.
- Model Architecture.
- Training Process
- Learned Parameters
- Output or Predictions

2.1 Input data: In our project focused on exploring women's mental insecurities, we utilized a Google Form survey as our primary data collection tool. The survey was specifically designed to capture insights into various aspects contributing to women's mental insecurities, encompassing questions related to skill enhancement, finance, gender discrimination, and social expectations.

The survey questionnaire was carefully crafted to address key dimensions that are known to influence women's mental well-being. Questions pertaining to skill enhancement aimed to understand respondents' perceptions of their professional growth opportunities and the impact on their confidence levels. Finance-related questions delved into financial stability, economic empowerment, and the stressors associated with financial

Furthermore, the survey included inquiries about experiences of gender discrimination in different contexts, such as the workplace, education, and society at large. These questions aimed to shed light on the prevalence and effects of gender-based inequalities on women's mental health. Additionally, inquiries regarding social expectations sought to explore societal pressures, stereotypes, and cultural norms that may contribute to women's feelings of insecurity and inadequacy.

By incorporating these specific themes into our survey design, we aimed to gather comprehensive data that would inform the development of our model architecture. The responses obtained through the Google Form survey served as the foundational input for our analysis, enabling us to identify patterns, correlations, and insights relevant to understanding and addressing women's mental insecurities.



Basic flow for building the machine learning (ML) model

2.2 Model architecture: Model architecture refers to the overall structure, organization, and connectivity of a machine learning model. In our project on women's mental insecurities, we conducted a survey using Google Forms to gather data on various factors contributing to mental well-being.

Here is how we incorporated the model architecture into our project:

1. Data Collection and Preparation:
We collected survey responses from women using a Google Form questionnaire.
After data collection, we performed preprocessing steps include encoding categorical variables.
2. Feature Engineering:
From the survey responses, we extracted and selected relevant features pertaining to skill enhancement, financial status, experiences of gender discrimination, and perceptions of social expectations.

3. Model Selection:
For predicting women's mental insecurities, we chose three models: logistic regression, support vector classifier (SVC), and random forest classifier.
Each model was selected based on its suitability for the task and its ability to capture different aspects of the data.
4. Model Training:
We trained each selected model on the pre-processed dataset, using a portion of the data for training and the rest for validation.
Hyperparameters for each model were optimized using cross-validation to improve performance.

By integrating this model architecture into our project, we were able to effectively analyse survey data, build predictive models, and deploy them for practical applications in addressing women's mental insecurities.

2.3 Training Process:

Data Splitting: - Partitioned data into training, validation, and test sets to prevent overfitting n and assess generalization.

Training: - Utilized gradient descent for logistic regression, kernel functions for SVC, and ensemble learning for random forest. Employed scikit-learn for efficient implementation.

Hyperparameter Tuning: - Optimized parameters like regularization strength for logistic regression, kernel and regularization parameters for SVC, and tree-related parameters for random forest via cross-validation.

Model Validation: - Evaluated models on validation set using accuracy, precision, recall, and F1-score. Analysed performance using ROC and precision-recall curves.

Iterative Refinement: - Iteratively adjusted models based on validation results to enhance performance before final evaluation on the test set.

2.4 Learned Parameters

2.4.1 Logistic Regession

model = LogisticRegression(solver='liblinear')

1) Logistic Regression Model Initialization: In our project, we setting up a method to predict outcomes using logistic regression. It is particularly useful for classification tasks where the dependent variable is categorical. It is a statistical technique used to make predictions, especially when the outcome has two possible values (mentally insecure/secure). We are choosing a specific method (or "solver") called 'liblinear' to help our model find the best fit.

2) solver: The solver parameter specifies which solver algorithm to use. In this case, it is set to 'liblinear'.'liblinear' is one of the solvers available in scikit-learn. It is particularly suitable for small datasets and binary classification problems

2.4.2 Support Vector Classifier

svc = SVC()
parameters = [{"kernel": ["rbf"], "gamma": [1e-4], "C": [200, 100, 10, 1.0, 0.01]}]

1) `SVC` class, which is the Scikit-learn implementation of the Support Vector Classification algorithm. The `SVC` class is typically imported from `sklearn.svm`. Without any parameters, it initializes the classifier with default settings.
2) When initialized without any parameters, the SVC class uses default settings for the SVM model. This means it will use a radial basis function (RBF) kernel by default, which is commonly used for non-linear classification tasks. Other parameters like regularization parameter (‘C’), kernel coefficient (‘gamma’), kernel type, etc., are set to default values as well.
3) The SVC class can accept various parameters to customize the SVM model according to the specific requirements of the task. Some commonly used parameters include:

- **C**: Regularization parameter. It controls the trade-off between maximizing the margin and minimizing the classification error. Higher values of C allow more flexibility in the decision boundary but may lead to overfitting.
- **kernel**: Specifies the type of kernel function to be used. Common choices include 'linear', 'poly', 'rbf' (default), 'sigmoid', etc.
- **gamma**: Kernel coefficient for 'rbf', 'poly', and 'sigmoid' kernels. It defines how much influence a single training example has. Higher values of gamma lead to more complex decision boundaries.

2.4.3 Random Forest Classifier

rfc = RandomForestClassifier(random_state = 42)
parameters = {
'n_estimators': [500],
'max_features': ['log2'],
'max_depth' : [4,5,6],
'criterion' :['entropy'] }

1. RandomForestClassifier Initialization:
- RandomForestClassifier is a supervised learning algorithm that constructs a forest of decision trees during training and outputs the class that is the mode of the classes predicted by the individual trees (classification) or the mean prediction (regression).

- `random_state=42`: This parameter ensures reproducibility of results by setting a fixed seed for the random number generator. It guarantees that the same sequence of random numbers is generated each time the code is executed, which is crucial for obtaining consistent results, especially during model evaluation and comparison.

2. Parameter Specification:
- `n_estimators`: This parameter determines the number of trees in the random forest. Each tree contributes to the final decision through a voting mechanism. By specifying `[500]`, we're setting the number of trees to 500. A higher number of trees can lead to better performance but also increases computational cost.
- `max_features`: This parameter controls the number of features considered for splitting a node. `'log2'` sets the maximum number of features to the base-2 logarithm of the total number of features. Other common options include `'auto'` (which is equivalent to `'sqrt'`), `'sqrt'`, and `None`. Using `'log2'` helps in controlling the model's complexity.
- `max_depth`: This parameter determines the maximum depth of each decision tree in the forest. It restricts the depth of the tree, thereby limiting its complexity and potential overfitting. By specifying `[4, 5, 6]`, we're exploring different tree depths during hyperparameter tuning.
- `criterion`: This parameter specifies the function used to measure the quality of a split. `'entropy'` is a measure of impurity that quantifies the amount of disorder in the data at a node. Other common options include `'gini'`, which measures the Gini impurity. Choosing `'entropy'` aims to build trees that are more balanced and informative in terms of splitting decisions.

2.5 Output Or Predictions:

2.5.1 Gender Discrimination: Gender discrimination remains a pervasive issue in workplaces around the world, significantly affecting the professional lives of women. despite advancements in gender equality, working women continue to encounter various forms of discrimination, leading to a range of insecurities. This essay explores the challenges faced by women in the workforce, shedding light on the insecurities that result from gender discrimination. Of the surveyed women, 47.94 percent reported feeling insecure about gender discrimination, while 52.05 percent expressed feeling secure in this regard.

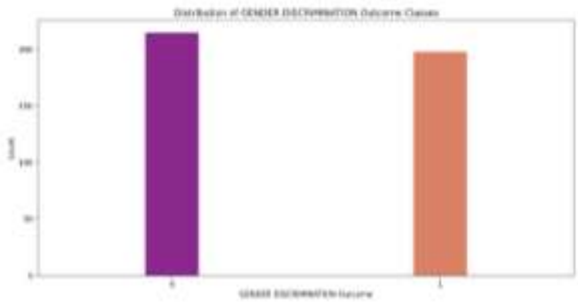


Fig 2.1 Gender Discrimination Outcome

2.5.2 Skill Enhancement: women often encounter unique obstacles that hinder their ability to acquire and develop new skills in the workplace. This essay explores the skill enhancement issues specifically faced by women and highlights the importance of addressing these challenges for fostering a more inclusive and competitive workforce. Out of the women surveyed, 61.50 percent indicated insecurity regarding skill enhancement in the workplace, whereas 38.49 percent conveyed a sense of security in this domain.

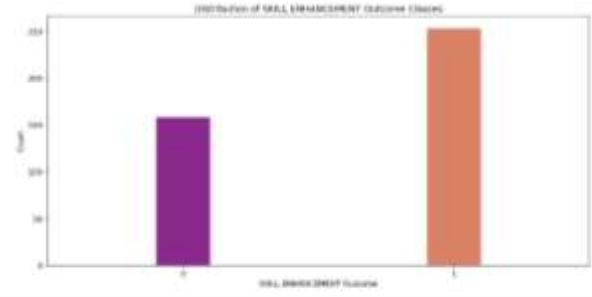


Fig 2.2 Skill Enhancement Outcome

2.5.3 Finance: Women globally still encounter distinctive financial hurdles that affect different facets of their lives. Whether in the professional sphere, managing personal finances, or planning for retirement, women regularly confront obstacles that impede their economic stability. This essay delves into the financial difficulties frequently experienced by women across their lifespan and assesses the ramifications of these obstacles on their financial welfare. The survey reveals that 65.13 percent of women feel financially insecure, while 34.86 percent feel financially secure.

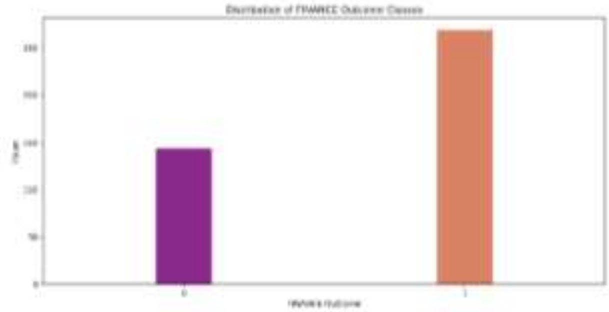


Fig 2.3 Finance Outcome

2.5.4 Social Expectations: Women in the workforce navigate a multifaceted environment where societal norms frequently intersect with their career ambitions. Expectations related to gender roles can exert a considerable impact on women's workplace encounters, influencing their decisions regarding careers, opportunities for advancement, and overall fulfilment. 56.90 percent of women express insecurity regarding social expectations, while 43.09 percent feel secure in this aspect.

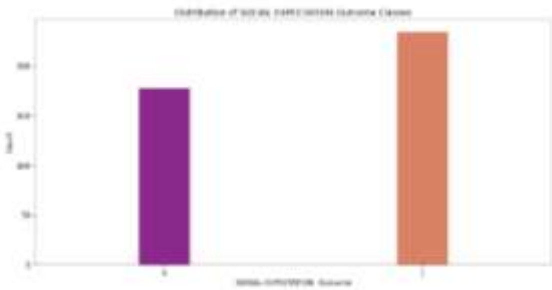


Fig 2.4 Social Expectation Outcome

III. RESULT

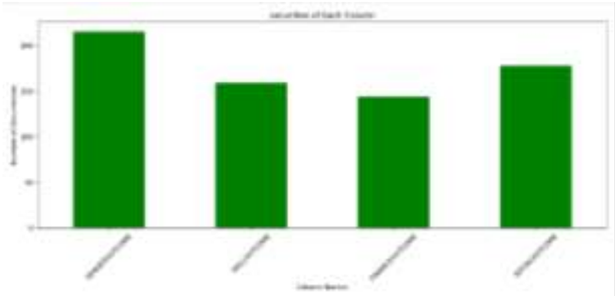


Fig 3.1 Securities of each Section

The survey findings (Fig 4.1) indicate that women are experiencing reduced levels of insecurity regarding gender discrimination. This improvement is particularly notable when contrasted with their concerns about financial stability, skill enhancement, and meeting societal expectations. In essence, while challenges related to discrimination persist, women seem to feel more assured in tackling these issues compared to their anxieties regarding financial security, skill development, and societal pressures.

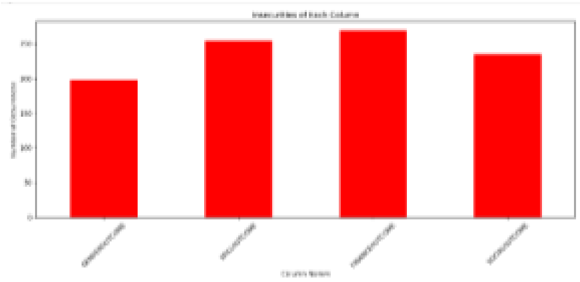


Fig 3.2 Insecurities of each Section

The data collected (Fig 4.2) suggests that women tend to experience mental insecurities that are primarily centered around financial concerns. women frequently express concerns about skill enhancement, indicating a desire to improve their abilities, knowledge, and expertise in various areas. the data highlights that societal expectations also play a significant role in contributing to women's mental insecurities.

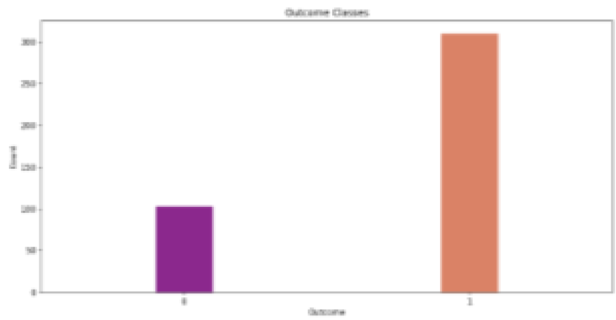


Fig 3.3 Overall Outcome Classes

From the (Fig 4.3) Based on the survey data collected, this project concludes that women in various societal contexts, including those within the workforce and those without jobs, tend to experience greater feelings of insecurity rather than security.

IV. CONCLUSION

In conclusion, the survey findings paint a complex picture of women's experiences with insecurity, particularly in relation to gender discrimination, financial stability, skill enhancement, and societal expectations. While there has been a noticeable improvement in women feeling more assured in tackling issues of gender discrimination, they continue to grapple with significant insecurities, particularly regarding financial stability, skill development, and societal pressures. The data underscores that mental insecurities are predominantly centered around financial concerns, with women expressing a strong desire to enhance their skills and navigate societal expectations. Overall, this project concludes that women across various societal contexts, whether in the workforce or not, tend to experience greater feelings of insecurity rather than security. These insights shed light on the multifaceted challenges that women face and emphasize the ongoing need for targeted interventions to address their diverse concerns and promote greater empowerment and well-being.

V. REFERENCES

[1] International Journal of Science and Research (IJSR) ISSN: 2319-7064 ResearchGate Impact Factor (2018): 0.28 | SJIF (2018): 7.426 Volume 9 Issue 1, January 2020 www.ijsr.net Licensed Under Creative Commons Attribution CC BY Machine Learning Algorithms - A Review Batta Mahesh

[2] https://www.javatpoint.com/machine-learning-models/

[3] Altshuler, L., Mintz, J., & Leight, K. (2002). The life functioning questionnaire (LFQ): a brief, gender-neutral scale assessing functional outcome. *Psychiatry Research, 112*(2), 161–182.

[4] https://link.springer.com/chapter/10.1007/978-3-319-18305-3_1