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Research Article

Cognitive Framework to Identify Women Empowerment using Swarm Enhanced Neural Networks

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ABSTRACT

Women are contributing equally with males to the development of a healthy family, society, and nation. One indication of women's empowerment is socioeconomic level. This study is an innovative one concentrated on the classification and comparison of Socio-Economic Status (SES). Women along the evolution of a cognitive model. Many factors affect the socioeconomic level of women; consequently, an artificial neural network (ANN) model using Fire Work Optimization (FWO) is used to detect, forecast, and classify this status. Operating for optimization, FWO uses swarm intelligence. Training ANN for classification goals using FWO. The results of the experiment prove that FWO-ANN performed more efficiently giving 99.34 percent accuracy in classification. Other swarm optimization methods, such as Particle Optimization (PSO) and Cat Swarm Optimization (CSO), were not as accurate or efficient as the current model.

Keywords: Artificial Neural Network, Fire Work Optimization, Swarm Intelligence, Cat Swarm Optimization

I. INTRODUCTION

In today's world of growing technology, women are holding prominent job positions in all fields, along with men. Quick progress is made when the government creates programs to give women more power and improve their social and economic situations growing the wealth of the country. The focus of this study is on the social status and economic condition of women [1]. SES gauges a woman's degree of life fulfillment.

It significantly influences children's and families' quality of life as well. Everywhere women are subjected to discrimination and are not let to lead fulfilling lives. Higher socioeconomic background women are more knowledgeable about health care, nutrition, better housing, education, and decision-making according to the UN report. Higher socioeconomic level women are more likely than lower socioeconomic level women to be independent across different nations. Most research conducted nowadays examine how women's socioeconomic level influences their families, their children, and the national development [2]. Giving women more authority follows naturally from raising their financial situation. Based on their education, income, and employment, a person's socioeconomic level—that is, their social class—as stated by the American Psychological Association as follows: Assessing the socioeconomic status of women in India is more complex due to the influences of multiculturalism, customs, and religion. It is also affected by geographical factors and familial traditions. Current research employs artificial ANN with FWO for the classification of women's SES[6].

The aim of the study is to categorize the SES of women in India utilizing ANN with the FWO algorithm. The study seeks to determine the most influential characteristics impacting SES across various regions of India and their correlation with other attributes through feature mining and association rule mining. The subsequent sections of the paper are structured as follows Section II examines pertinent literature and highlights deficiencies in current systems. Section III delineates the proposed methodology, encompassing the dataset, feature selection, and the ANN model utilizing the FWO Swarm algorithm. Section IV delineates the experimental findings and their analysis. Section V examines the findings and their implications. Ultimately, Section VI finishes the work with essential insights and prospective avenues.

II. LITERATURE SURVEY

Forecasting dynamic urban growth in Guilford County, USA, the study applied an improved support vector machine (SVM) model with an RBF kernel over a 19-variable dataset. The study aimed to assist companies and governments in policy development to minimize unfavorable effects in fast urbanization. Although the model, with 85% accuracy on test data, neglected socioeconomic factors or address women-specific classifications, leaving a vacuum in constructing comprehensive SES models, appropriate for urban settings [1]. This work uses street-view pictures acquired from Google Street View (GSV) in Brazil to forecast socioeconomic (SE) indices using deep learning. Training a CNN using the photos as input data yielded 80% accuracy for higher income classes. Its application to more general SES categories, especially those needing individual-level characteristics [2], is limited, nevertheless, by the dependence on visual and geographical data. The study used US Daily Poll and Census Bureau data to estimate veterans' physical well-being using machine learning methods, most specifically gradient boosting. In SES prediction the model achieved 804% accuracy. But the study focused only on health outcomes and ignored more broad SES forecasts or data particular to women [3]. utilizing a multicounty dataset, the study investigated utilizing SES and COVID-19 frequency. COVID-19 instances were predicted using supervised machine learning models including Adaptive Boosting, Random Forest, and Linear Regression. Utilizing data from SE indicators and Human Development Metrics, the study examined attribute distribution, correlations, and outlier detection obtaining a highest prediction accuracy of 76%. Useful for data analysis connected to pandemics, the study paid little attention to thorough SES categories and women-specific applications [4].

Combining several machine learning approaches with statistical analytic strategies, this paper evaluated using a Rajahmundry, India dataset, SES levels in every rural area. The method obtained a SES classification with total accuracy of 9667%. Still, it paid minimal attention to gender-specific insights or sophisticated optimization strategies [5]. The study underlined the challenges of fast urbanization, which increases the SES discrepancy even while it promotes economic growth. The scientists addressed this difficult issue by collecting satellite images taken using remote sensing technologies into a CNN to forecast SES gaps in French cities. Regarding metropolitan areas, the plan worked well and produced positive results. Still, it neglected family- or personal-level socioeconomic aspects unique to women [6]. The study analyzed key factors affecting the survival index in sub-Saharan Africa, focusing on education, sex of the child, wealth, and parental education as primary indicators. Machine learning algorithms such as Deep Survival Network (Deep Surv) and Random Survival Forest (RSF) were applied to the dataset, achieving 80% accuracy in associating survival outcomes with these SES factors. While the study effectively identified important determinants, it did not address women-centric SES prediction or classification [7].

The study focused on individual income classification using a mobile phone buyers' dataset. Features such as phone usage, top-up style, handset model, social network activities, and individual portability were used as input factors. Deep learning was applied, achieving an accuracy of 72%.

However, the study relied on a single data type and did not incorporate multidimensional factors like education and family background, making it less ideal for comprehensive SES prediction [8]. The authors used data from French Twitter users, including factors like tweet semantics, social networks, habitat, and occupation, to infer SES using machine learning algorithms. They noted that SES relied on a combination of individual attributes, environmental circumstances, and social networks. While the model worked effectively in investigating social inequality and satisfaction, it neglected personal and family-level socioeconomic issues, particularly those crucial to women [9]. Various machine learning approaches were deployed utilizing family expenditure and income survey data to classify poverty degrees in Jordan. The LightGBM approach scored 81% F1-wise. Although the study produced some interesting findings, it neglected women's SES and lacked novel optimization techniques to increase the accuracy of the forecasts [10]. Based on extant infrastructure, the study categorized SES using satellites in various locations. some pictures and CNN. Although the study obtained accurate figures at the area level [11], it neglected socioeconomic issues at the person level or those particular to gender. Using SES elements, the paper investigated, via machine learning systems in healthcare, how socioeconomic bias influences Finding means to forecast when a child's asthma might aggravate was the aim.

The data revealed via machine learning that children from low-SES backgrounds were more likely to have asthma than those from higher-SES backgrounds. This amply demonstrates how SES influences children's health. Although the study examined health data, it did not examine using alternative sets of characteristics or predicting or classification of SES for women [12].

Using data mining methods, the ARIMA model, and Big Data, the study projected social and economic dynamics leading to Ukraine's GDP. The forecasts were rather consistent. Although the survey lacked information on how to categorize SES by gender or by individual [13], it provided us essential information for developing more general forecasts on the society and economy. Using elements including money, education, and employment, the study sought to modify the nonlinear link between women's height and SES. The Bayesian neural network performed the best of seven machine learning techniques applied. Still, the data revealed a weak nonlinear connection between women's SES and height. The study [14] concentrated just on height, one factor. Though it was largely about women, it did not apply any Sophisticated optimization techniques or thorough SES categorization. SES must be immediately addressed in emerging nations since there are significant disparities even with many government-run economic initiatives under progress. The study sought to determine the socioeconomic level of rural residents by examining their income levels. It provided these locations with relevant knowledge. It did not, however, concentrate on SES variations between men and women or apply innovative artificial intelligence techniques to provide more precise forecasts [15]. Most published research demonstrate a relationship between SES and mental and physical health by use of statistical analysis or simple machine learning techniques.

These studies are typically quite erroneous most of the time, and the techniques applied barely approach SES. Moreover, especially with regard to ANN employing optimization methods, there is a clear dearth of research aiming mainly at SES categorization and prediction for women. Here you have a fantastic potential for creativity.

Neither a manual nor an automatic system can guess the SES of women. Dependency on hand-made decision-making procedures can lead to errors and delays, therefore lessening the value of support programs. This disparity in how things are assessed and classified could result in poor utilization of resources and complicate the process of attaining objectives meant to provide women greater authority and change their social and economic circumstances. These studies close that void by precisely forecasting and identifying women's SES using a complete set of features. They accomplish this utilizing a Firework Optimization Swarm approach in tandem with an ANN model.

III. EXPERIMENTAL SETUP

Nearly thirty features are carefully chosen to build the training dataset. The proposed model discussed in this paper overcomes the issues of delays and inaccuracies, predicting and classifying the SES of women into low, medium, and high automatically using Artificial Intelligence. This model represents an AI application for Social Development and Women Empowerment, utilizing ANN with swarm intelligence.

A. Data Acquisition

The factors influencing SES of women involve many factors ranging from personal data, education data, income, age, marital status, place of residence, province, community, family type etc., These factors are heterogeneous and distributed. The feature values are acquired through online form. Features Considered for building dataset are listed in Table 1.

Table 1. Features considered for building dataset

Age	Mother (housewife/working)	Age at the time of marriage	Father's education	Involved in family decision
Place of birth	Number of Family members	Number of children	Ancestral Property owned	Belong to Tribal area
Gender	Family Type (Joint /Nuclear)	Marital Status	Family Income	Number of dependents
Religion	Community (BC/OBC/GM)	Education	Mother's education	Personal Income
Residence in rural area	Major health issues in family member if any	Employed/Entre preneur/Self employment	Marital status	Family Background (Agriculture/ Non agriculture)
Province (City/Metropolita n)	Family member addiction to alcohol	Not Employed	Self-Property owned	Father's/Husban d Income

B. Data preprocessing

Data is heterogeneous consisting of different data types, which is the major challenge faced. The values of the features are assigned values from 0 to 9. For example, province is assigned value 0 for city and 1 for metropolitan. Each religion is assigned with unique numbers between 0 to 9. For yes/ no type of features, 1 for yes and 0 for no are assigned. Features of Boolean type follow the same technique. For income range is considered and suitable value supplied for every range. The whole data set is eventually refined to get consistent values that may be applied for model construction.

C. Data transformation and scaling

All Box Cox transformation is used to acquire improved normal distribution of features by means of data transformation approach. Data scaling follows then to attain consistency of values. The Min Max Normalization method is applied on the features by matching the scalar data to whatever feature it is relevant for.

D. Artificial Neural Network (ANN)

The mathematical depiction of nature endowed biological neurons discovered in humans is ANN. Natural occurring neurons are replicated in ANNs. Single perceptron cannot handle complex problems hence multiple perceptron is arranged to form Multi Layered Perceptron (MLP) and thus the model is called ANN with MLP. This cluster of perceptron works together to provide a very powerful learning environment for advanced applications like recognition of speech, shape, image etc., and in prediction and classification problems. Here Feed Forward Neural Network is considered where the information flows in forward direction from input layer to output layer through hidden layer. Figure 1 shows the architecture of ANN.

Deciding upon the number of perceptron in the input layer is dependent on the complexity of the underlying problem, number of features in consideration, feature types and its quality. Choosing the number of nodes in hidden layer is very challenging as choosing a very large number creates over fitting which performs well (gives less error value) on training data and fails on test data (gives high error value). On the other hand, if a very smaller number of nodes is chosen, it may lead to problems under fitting and both training and test data will fail to produce accurate results resulting in high error value. Hence, choosing the optimum number of neurons depends on the number of inputs and number of outputs to be generated. Weights control the neural network.

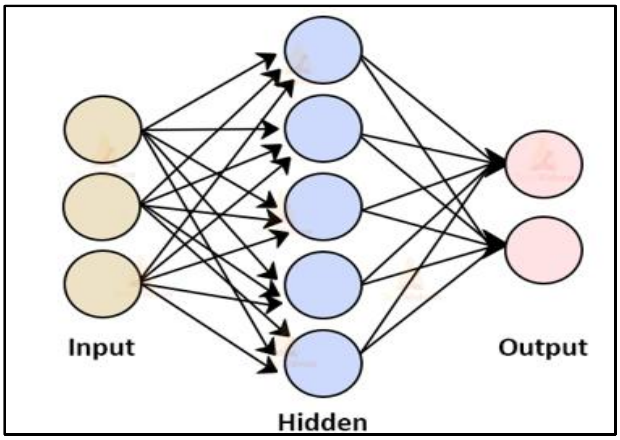

Fig. 1.Architecture of ANN

In the beginning, some random values are set for weights and as the training progresses, the values are adjusted and updated after the completion of iterations. The main target of training is to get the right combinations of weights for nodes so that error value is lowest. Hidden layer works using activation function which brings nonlinearity to the ANN. Both linear and nonlinear activation functions exist. Linear functions Sigmoid activation function is used for the current model.

Activation function is vital part of Neural Network (NN) and they introduce non- linearity to the NN. Neurons are composed of activation function, bias, and weight. Activation function decides the firing of neurons. Every input undergoes non-linear transformation before transmitting to the next layer. The output is given by equation (1)

$$\text{output} = \text{Activation } \sum(\text{weight} * \text{input}) + \text{ bias} \text{ ---- (1)}$$

Sigmoid is the most used nonlinear activation function in the learning process. The data will be transformed in between 0 and 1. The output is given by equation (2)

$$f_x = \frac{1}{(1+e^{(-x)}-1)} \text{ ---- (2)}$$

Loss function measures the training performance of neural network by comparing target and predicted values of the output. The main goal of NN is to reduce the difference between predicted and actual output. In this model Mean Square Error (MSE) is used. For every output of the NN, it finds the difference with the true label, squares it and finally takes the average. MSE is given by equation (3)

$$MSE = \frac{1}{N} \sum_1^N (y_i - \hat{y}_i)^2 \text{ --- (3)}$$

IV. EXPERIMENTATION

During training, the model is run with an initial set up and the output obtained is compared with the target output. The error is calculated by the difference between the actual and target output. If the error value is high, the weights are adjusted, so that we get minimum error. Training involves altering the number or size of hidden layers, trying out different activation functions and running with different epochs size. The process is repeated until the error is lowest. The goal of ANN training is to attain an optimum learning rate for a set of inputs to get desired output. For tanning 80% (1600) of the data set is considered and the remaining 20% (400) is used for validation or testing purposes.

A. Fire work Optimization-Swarm algorithm

FWO was introduced in the year 2010. It imitates the explosion of real time firecrackers in space. Exploding space is compared to searching space to obtain optimization. Working of FWO is explained in below steps

1. Fireworks are placed in different random positions say l Equation (4).

2. Fireworks are exploded to get sparks.

3. Sparks are examined to get the best spark Equation (5) and it is marked as best location and algorithm is halted. Otherwise go to step4.

4. Different position l from the recent sparks are selected for exploding next fireworks and step 2 and step 3 are applied until best spark position is found.

Fireworks quality is judged using the following parameters.

1. Firework is termed of good quality if it can generate many sparks around the explosive point.

2. Firework is bad if it generates only few sparks around exploding point.

Good quality fireworks help in obtaining favored location in the search space whereas bad quality fireworks encourage to explore new locations in the search space.

$$S_l = k \cdot \frac{z_{max} - f(m_l) + \alpha}{\sum_{l=1}^{P}(z_{max} - f(m_l)) + \alpha} \quad \text{-----(4)}$$

$$U_l = r \cdot \frac{f(m_l) - z_{min} + \alpha}{\sum_{l=1}^{P}(f(m_l) - z_{min}) + \alpha} \quad \text{-----(5)}$$

$$s_l = \begin{cases} round(h,k) \ if \ s_l < hk, \\ round(j,k) \ if \ s_l > jk, \\ round(s_l) \ other \ wise \end{cases} \quad \text{----(6)}$$

Where:

S_l is number of sparks at location l

U_l intensity of explosion at location l

k and rare constants to control the total number of sparks

z_{max} = max(f(m)) is the worst value of the firework m_l

and z_{min} = min(f(m)) is the best value of the firework m_l,

α keeps denominator greater than zero.

Constants h and j limits spark numbers.

B. Implementation of ANN-with-FWO

The efficiency of ANN can be optimized with respect to speed of convergence and accuracy by applying FWO technique. ANN is double empowered with the local search capability of ANN and global search capability of FW which helps in obtaining good results by eliminating local maxima. FWO algorithm is applied to get initial configuration of ANN. The optimized value of bias and weights are decided based on the optimum value of the fitness function returned by FWO. As mentioned, MSE is used as an objective function to minimize error. The parameter setting of FWO is given in Table 2. ANN is run with the FW optimized values of weights and bias on the training set. The error value is noted. In the second step, the weights and bias are once again re optimized to get minimized value for objective function to improve the performance of ANN in classification.

Table 2. Attributes of Fire work Algorithm

Attributes	**Name**	**Value**
Number of Fireworks	P	7
Max iteration	Bmax	100
Intensity factor	r	30
Sparks factor	K	40
Maximum sparks	Hk	45
Minimum sparks	Jk	20
Maximum limit	Zmax	0
Minimum limit	Zmin	1

V. RESULTS AND DISCUSSION

From graph shown in Figure 2 and Table 3. the high classification accuracy with less MSE is achieved at faster rate using FWO on ANN. The model is compared with other optimization algorithms like with PSO and CSO with and without FWO and following observations are obtained. Table 4 shows the details of comparative analysis of MSE and Accuracy values of FWO, PSO and CSO algorithms on ANN. Comparison chart shown in Figure 3. FWO outperformed in comparison with the latter two optimization algorithms with 99.34% accuracy in predicting SES with minimal MSE of 0.2.

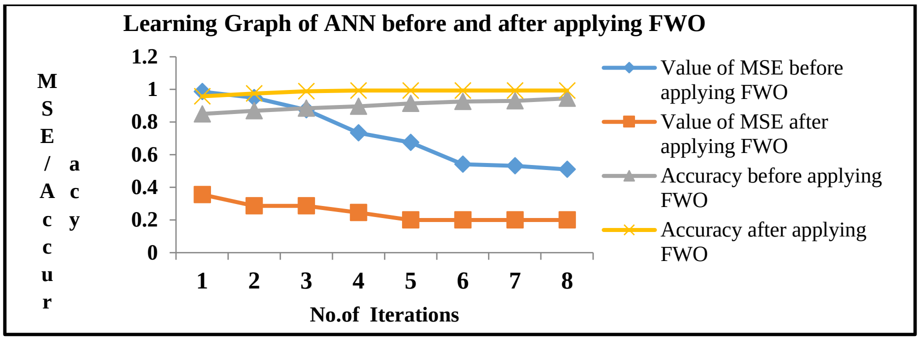

Fig.2. Learning graph of ANN

Table 3. MSE and Accuracy score of ANN

Iterations	Value of MSE before FWO	Value of MSE after FWO	Accuracy before applying FWO	Accuracy after applying FWO
1	0.986	0.356	85%	95.78%
2	0.950	0.199	87%	97.56%
3	0.875	0.123	88.54 %	98.87%
4	0.734	0.20	89.55%	99.34%
5	0.675	0.20	91.34%	99.34%
6	0.541	0.20	92.54%	99.34%
7	0.532	0.20	93.02 %	99.34%
8	0.510	0.20	94.50 %	99.34%

Table 4. Comparison with other optimization algorithms

Optimization Techniques	Final Value of MSE	Final Value of Accuracy
PSO	0.345	98.45%
CSO	0.296	98.97%
FWO	0.20	99.34%

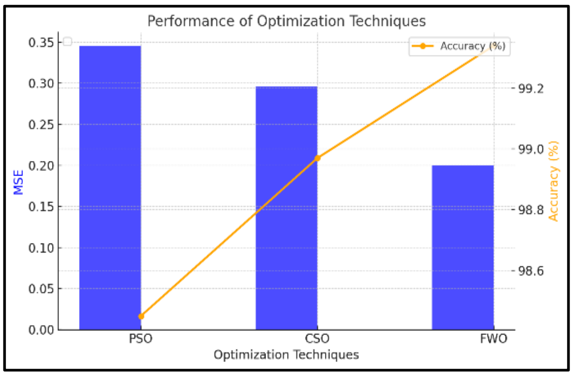

Fig.3. Comparison with other optimization techniques

Out of 400 test samples, most predictions are accurate, with only a few misclassifications per class (2-3 false predictions). This highlights the model's strong performance with an overall accuracy of 99.34%, while also reflecting a realistic distribution of minor errors. The confusion matrix shown in Figure 4 demonstrates the potential of the proposed model for high-accuracy SES classification.

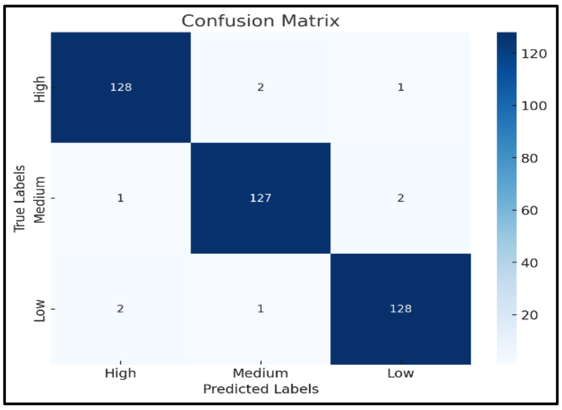

Fig.4. Confusion matrix showing SES classification

The investigation indicates that FWO markedly enhances the performance of ANN in comparison to PSO and CSO optimization methods. It attains a maximum accuracy of 99.34% while sustaining the minimal MSE value of 0.2, illustrating its efficacy in forecasting SES. Figure 2 shows how quickly FWO converges; as the number of rounds drops, accuracy steadily rises. Table 3 shows, especially in the fourth round, FWO greatly lowers MSE and improves accuracy. Table 4 compares accuracy and error reduction to show that FWO beats PSO and CSO.

VI. CONCLUSION

The ANN with FWO gives best performance result when compared with other optimization techniques and is successful in classifying the data set (1600 training data and 400 test data) of socio-economic status of women as high, medium, and low with classification accuracy of 99.34%. The model can be improved further using hybrid methods of optimization techniques. Currently model is applied at district level dataset, and it can be further applied for dataset at state and central level for classification of socio-economic status of women in India.

REFERENCES

[1] F. Karimi, S. Sultana, A. S. Babakan, and S. Suthaharan, “An enhanced support vector machine model for urban expansion prediction,” Computers, Environment and Urban Systems, vol. 75, pp. 61–75, 2019, doi: 10.1016/j.compenvurbsys.2019.01.001.

[2] J. Machicao, A. Specht, D. Vellenich, L. Meneguzzi, and R. David, “A deep-learning method for the prediction of socio-economic indicators from street-view imagery using a case study from Brazil,” CODATA Data Science Journal, vol. 21, 2022, doi: 10.5334/dsj-2022-006.

[3] C. A. Makridis, D. Y. Zhao, C. A. Bejan, and G. Alterovitz, “Leveraging machine learning to characterize the role of socio-economic determinants on physical health and well-being among veterans,” Computers in Biology and Medicine, vol. 133, Art. no. 104354, 2021, doi: 10.1016/j.compbiomed.2021.104354.
[4] W. L. Winston, M. McCann, and G. Onofrei, “Exploring socioeconomic status as a global determinant of COVID-19 prevalence, using exploratory data analytic and supervised machine learning techniques: Algorithm development and validation study,” JMIR Form Res., vol. 6, no. 9, pp. e35114, Sep. 2022, doi: 10.2196/35114.
[5] V. Balasankar, S. V. Penumatsa, and P. R. V. Terlapu, “Intelligent socio-economic status prediction system using machine learning models on Rajahmundry A.P., SES dataset,” Indian Journal of Science and Technology, vol. 13, no. 37, pp. 3820–3842, 2020, doi: 10.17485/IJST/v13i37.1435.
[6] J. L. Abitbol and M. Karsai, “Interpretable socioeconomic status inference from aerial imagery through urban patterns,” Nature Machine Intelligence, vol. 2, pp. 684–692, 2020, doi: 10.1038/s42256-020-00243-5.
[7] J. B. Nasejje, R. Mbuvha, and H. Mwambi, “Use of a deep learning and random forest approach to track changes in the predictive nature of socioeconomic drivers of under-5 mortality rates in sub-Saharan Africa,” BMJ Open, vol. 12, Art. no. e049786, 2022, doi: 10.1136/bmjopen-2021-049786.
[8] P. Sundsøy, J. Bjelland, B.-A. Reme, A. M. Iqbal, and E. Jahani, “Deep learning applied to mobile phone data for individual income classification,” in Proceedings of the 2016 International Conference on Artificial Intelligence: Technologies and Applications, Atlantis Press, 2016, pp. 96–99, doi: 10.2991/icaita-16.2016.24.
[9] J. L. Abitbol, M. Karsai, and E. Fleury, “Location, occupation, and semantics-based socioeconomic status inference on Twitter,” in 2018 IEEE International Conference on Data Mining Workshops (ICDMW), 2018, pp. 1192–1199, doi: 10.1109/ICDMW.2018.00171.
[10] Alsharkawi, M. Al-Fetyani, M. Dawas, H. Saadeh, and M. Alyaman, “Poverty classification using machine learning: The case of Jordan,” Sustainability, vol. 13, no. 3, Art. no. 1412, 2021, doi: 10.3390/su13031412.
[11] Shetty, A. Thorat, R. Singru, M. Shigawan, and V. Gaikwad, “Predict socio-economic status of an area from satellite image using deep learning,” in 2020 International Conference on Electronics and Sustainable Communication Systems (ICESC), 2020, pp. 177–182, doi: 10.1109/ICESC48915.2020.9155696.
[12] Y. J. Juhn et al., “Assessing socioeconomic bias in machine learning algorithms in health care: A case study of the HOUSES index,” Journal of the American Medical Informatics Association, vol. 29, no. 7, pp. 1142–1151, Jun. 2022, doi: 10.1093/jamia/ocac052.
[13] Y. V. Dehtiarova and Y. Yevdokimov, “Data mining methods and models for social and economic processes forecasting,” Marketing and Management of Innovations, vol. 80, pp. 96–99, 2018, doi: 10.21272/mer.2018.80.03.
[14] Daoud, R. Kim, and S. V. Subramanian, “Predicting women’s height from their socioeconomic status: A machine learning approach,” Social Science & Medicine, vol. 238, Art. no. 112486, 2019, doi: 10.1016/j.socscimed.2019.112486.
[15] M. Islam and M. Mustaquim, “Socio-economic status of rural population: An income level analysis,” Asian Academic Research Journal of Multidisciplinary, vol. 1, pp. 98–106, 2014.