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BODY FAT PREDICTION USING RELATIVE ERROR SUPPORT VECTOR MACHINE

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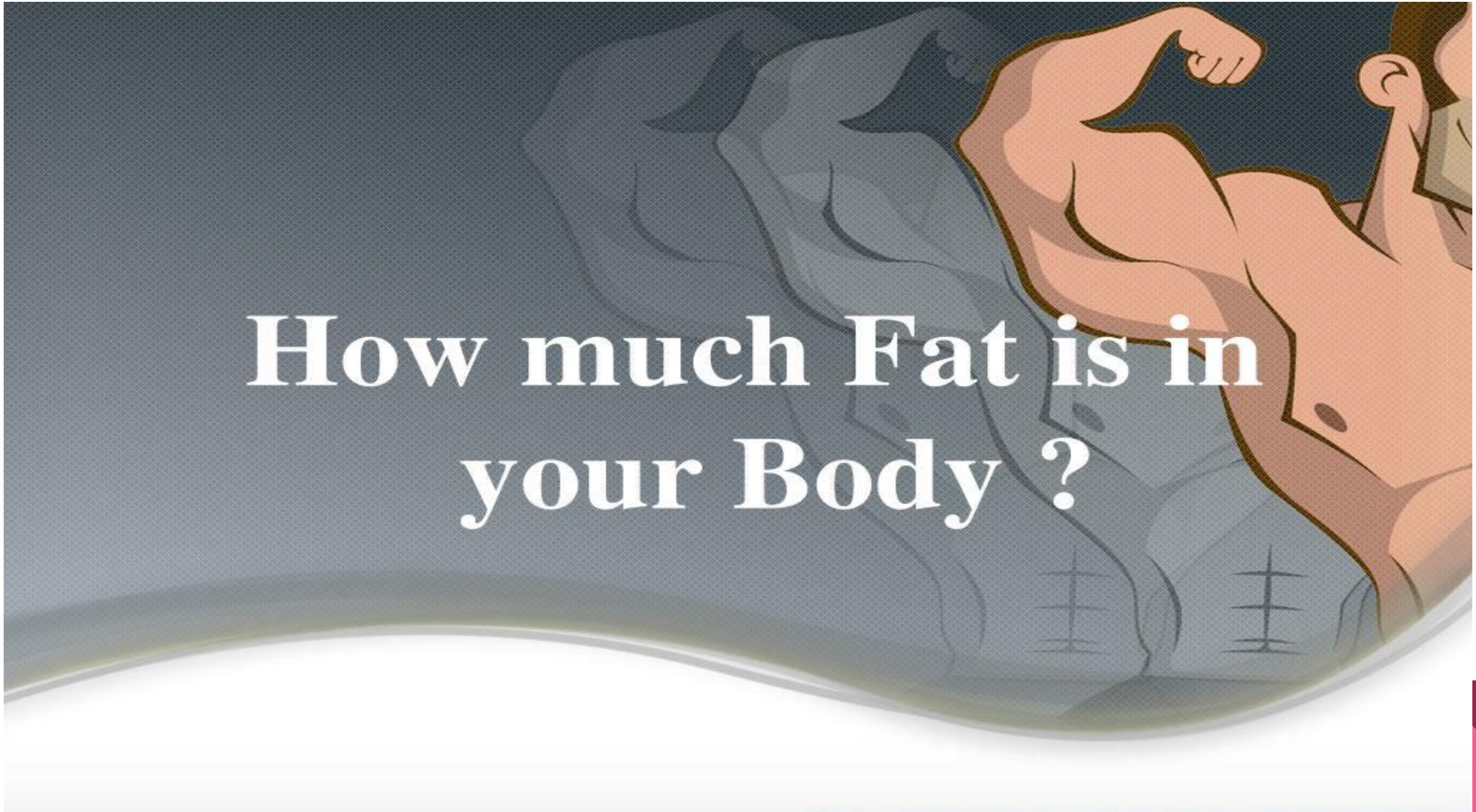

How much Fat is in
your Body ?

CONTENTS

INTRODUCTION

- Crucial for assessing health and disease risks, especially obesity-related.
- BMI lacks accuracy, unable to distinguish between fat and muscle mass.
- IRE-SVM offers a precise approach to estimating body fat percentage.
- Considers relative importance of different body measurements.
- Results in more accurate predictions.
- Revolutionizes fat prediction and provides valuable insights for personalized treatment.

Review of Literature

Author	Title	Publication	Observation
Cynthia L. Ogden, Margaret D. Carroll, Brian K. Kit, Katherine M. Flegal	Prevalence of Childhood and Adult Obesity in the United States	JAMA. 2014;311(8):806-814	Prevalence of Obesity: More than one-third of adults and 17% of youth are obese. Prevalence of Obese :More than one-third of adults and 17% of youth in the United States are obese.
Jian-Gao Fan, Seung-Up Kim, Vincent Wai-Sun Wong	New trends on obesity and NAFLD in Asia	Journal of Hepatology. 2017;67(3)	Prevalence and Incidence & Traditionally Western diseases, obesity and NAFLD are increasingly recognized in the Asian population due to urbanization .

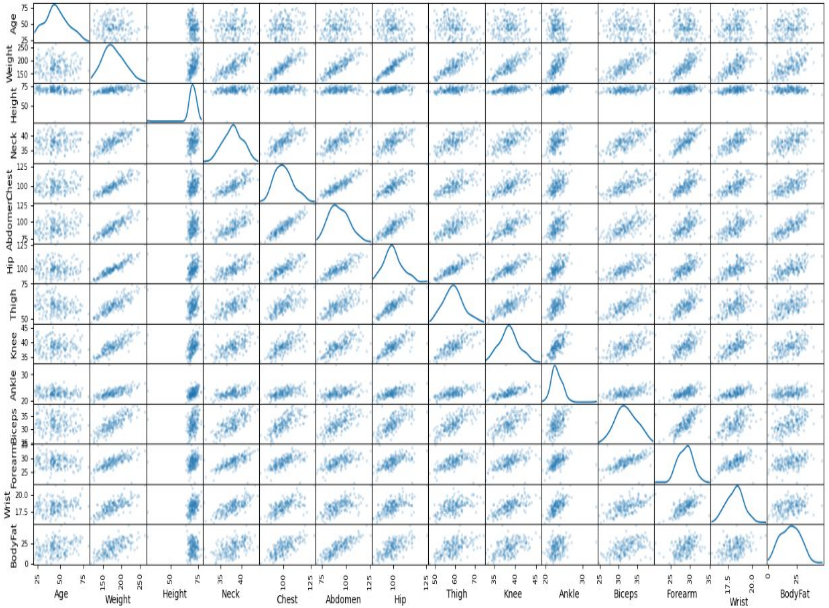
Author	Title	Publication	Observation
Zongwen Fan, Raymond Chiong, Zhongyi Hu, Yuqing Lin	A fuzzy weighted relative error support vector machine for reverse prediction of concrete components	Computers & Structures, Volume 216, November 2019, 106171	The paper introduces FW-RE-SVM to predict concrete components in reverse, crucial for resource optimization . Results showcase FW-RE-SVM's effectiveness in accurate prediction under various scenarios, promising practical applications in engineering projects.
Yitian Xu, Laisheng Wang	A weighted twin support vector regression	Knowledge-Based Systems, Volume 31, May 2012, Pages 1-7	Introduces a weighted variant of twin (TSVR) to address the issue of uniform penalties, enhancing generalization ability and effectiveness through experiments on artificial & benchmark data..

Analysis of Data

	Age	Weight	Height	Neck	Chest	Abdomen	Ankle
count	201.000000	201.000000	201.000000	201.000000	201.000000	201.000000	201.000000
mean	45.572139	178.077363	70.042289	37.961194	100.645274	92.625871	22.997015
std	12.721872	28.003221	3.930341	2.347613	8.503887	10.670132	1.574322
min	22.000000	118.500000	29.500000	31.100000	79.300000	69.400000	19.100000
25%	39.000000	157.750000	68.250000	36.400000	94.000000	84.400000	22.000000
50%	44.000000	176.000000	70.000000	38.000000	99.600000	90.900000	22.700000
75%	54.000000	198.000000	72.250000	39.500000	105.600000	99.800000	23.900000
max	81.000000	262.750000	77.750000	43.900000	128.300000	126.200000	33.700000

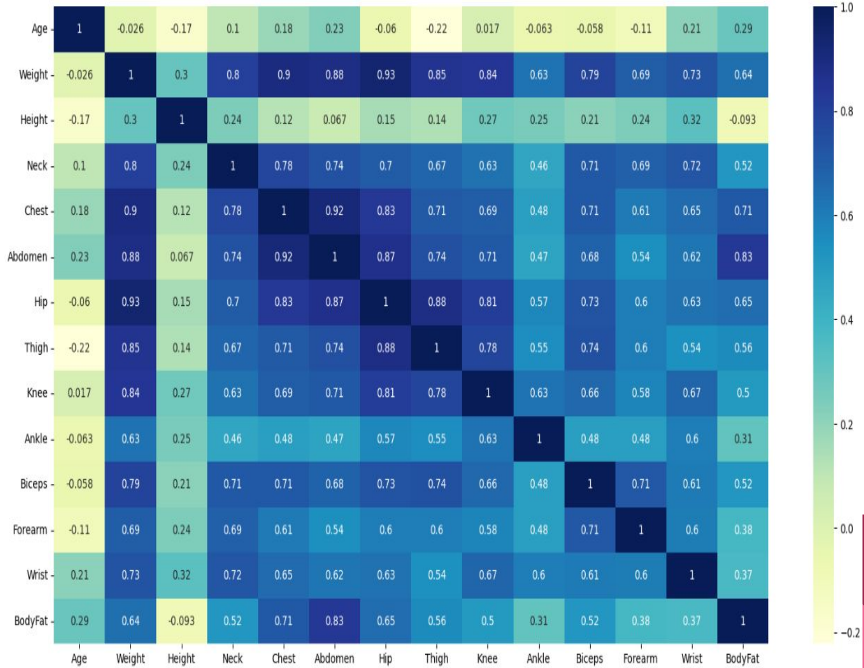
	Hip	Thigh	Knee	Wrist	BodyFat	Biceps	Forearm
count	201.000000	201.000000	201.000000	201.000000	201.000000	201.000000	201.000000
mean	99.790547	59.228358	38.562687	18.218905	19.435821	32.077612	28.681592
std	6.844637	5.132966	2.395694	0.919098	8.696517	2.950770	2.034849
min	85.000000	47.200000	33.000000	15.800000	0.000000	24.800000	21.000000
25%	95.400000	56.000000	37.100000	17.600000	12.400000	30.100000	27.300000
50%	99.300000	59.000000	38.400000	18.300000	19.600000	31.800000	28.800000
75%	103.700000	62.100000	40.000000	18.800000	25.800000	34.000000	30.000000
max	125.600000	74.400000	46.000000	21.400000	47.500000	39.100000	34.900000

The dataset consists of 252 samples, with 14 anthropometric measurements (age, weight, and various body circumference measurements) as input features, while the body fat percentage is the output feature.
Statistical description is provided.



Scatter Plot

Heat Map



Methodology

1. **Relative Error Support Vector Machine (SVM):**

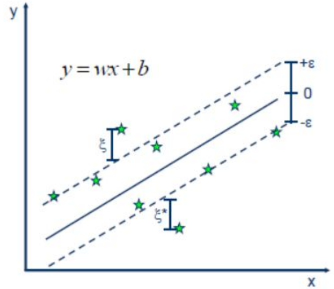
   - Tailored for body fat prediction, this method minimizes relative error between predicted and actual body fat percentages.

   - It considers the relative importance of different body measurements, enhancing prediction accuracy over traditional SVM approaches.

2. **Incorporation of Bias Term for IRE-SVM:**

   - This approach includes a bias error control term to mitigate any biases in the prediction model.

   - By controlling bias error, the model aims for unbiased and accurate predictions, capturing true underlying relationships effectively.



• Minimize:

$$\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N}\left(\xi_i + \xi_i^*\right)$$

• Constraints:

$$y_i - wx_i - b \le \varepsilon + \xi_i$$
$$wx_i + b - y_i \le \varepsilon + \xi_i^*$$
$$\xi_i, \xi_i^* \ge 0$$

Support Vector Machine for Regression

Relative Error SVM

$$\min_{\boldsymbol{w},b,\boldsymbol{e}} \frac{1}{2}\boldsymbol{w}^T\boldsymbol{w} + \frac{1}{2}C\sum_{i=1}^{N} e_i^2$$

$$\min_{\boldsymbol{w},b,\boldsymbol{e}} \frac{1}{2}\boldsymbol{w}^T\boldsymbol{w} + \frac{1}{2}C\sum_{i=1}^{N} e_i^2 + \frac{1}{2}\gamma b^2$$

Improved Relative Error SVM

$$e_i = \frac{y_i - (\boldsymbol{w}^T\phi(\boldsymbol{x}_i) + b)}{y_i}$$

Our predicted Model:

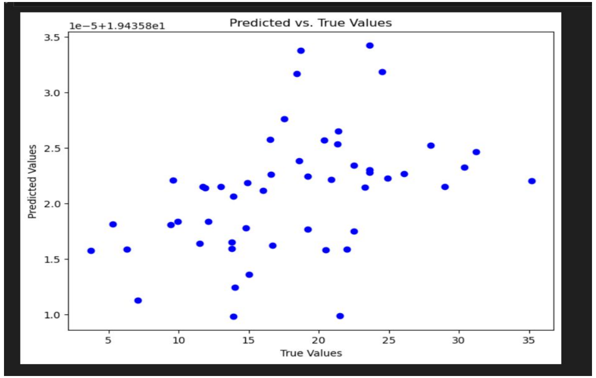
$$g(\boldsymbol{x}) = \boldsymbol{w}\phi(\boldsymbol{x}) + b = \sum_{i=1}^{N}\alpha_i K(\boldsymbol{x}_i, \boldsymbol{x}) + b.$$

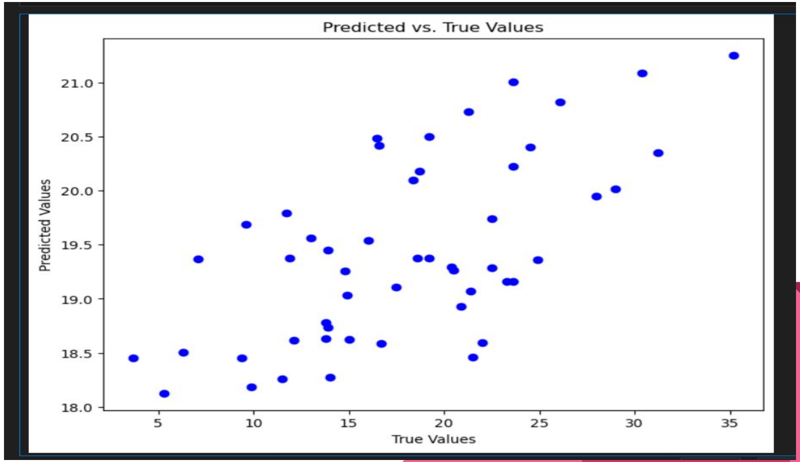
MODELS

Most effective model has larger diameter.

Summary of Results:

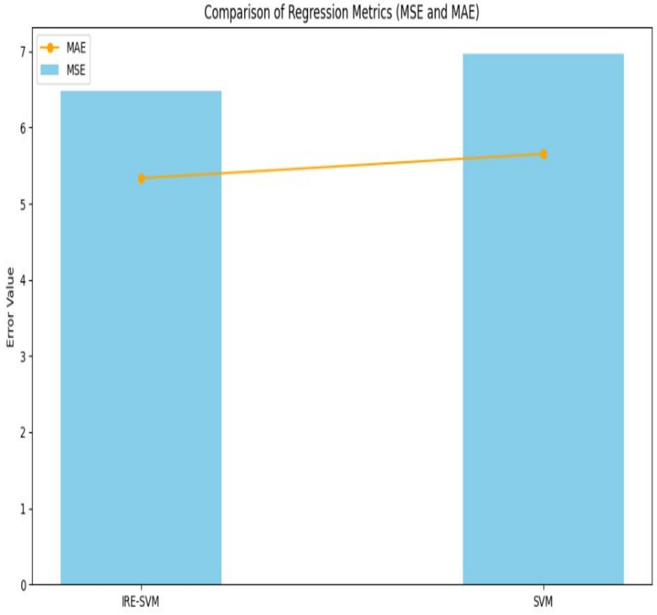
- The Improved Relative Error Support Vector Machine (IRE-SVM) model, with its lower Mean Squared Error (MSE) of 41.9500, outperforms the Relative Error Support Vector Machine (RE-SVM) model, which has an MSE of 48.1015.
- This superior performance is attributed to the incorporation of a bias error control term and parameter optimization in IRE-SVM. The lower MSE signifies its effectiveness in minimizing prediction errors and accurately predicting fat percentage.

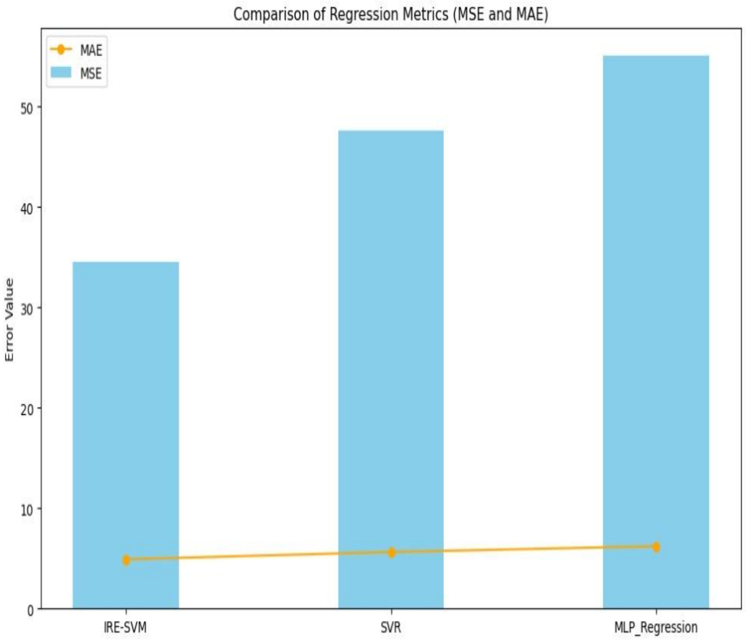




Summarry Results:

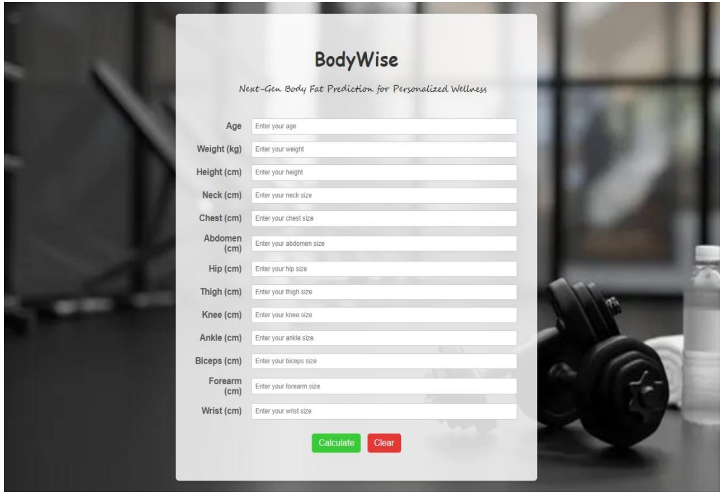
RE-SVM	IRE-SVM
Mean Absolute Error (MAE): 5.653380158854523 Standard Deviation (SD): 6.820415674656528 5 Root Mean Square Error (RMSE): 6.964307273072913 Robustness (MAC): 0.8747855017283774	Mean Absolute Error (MAE): 5.334373675478012 Standard Deviation (SD): 6.32290865854293 Root Mean Square Error (RMSE): 6.4768819267004 Robustness (MAC): 0.8913006691732553


Comparison of Regression Metrics (MSE and MAE)
MAE
MSE
Error Value
0
1
2
3
4
5
6
7
IRE-SVM
SVM

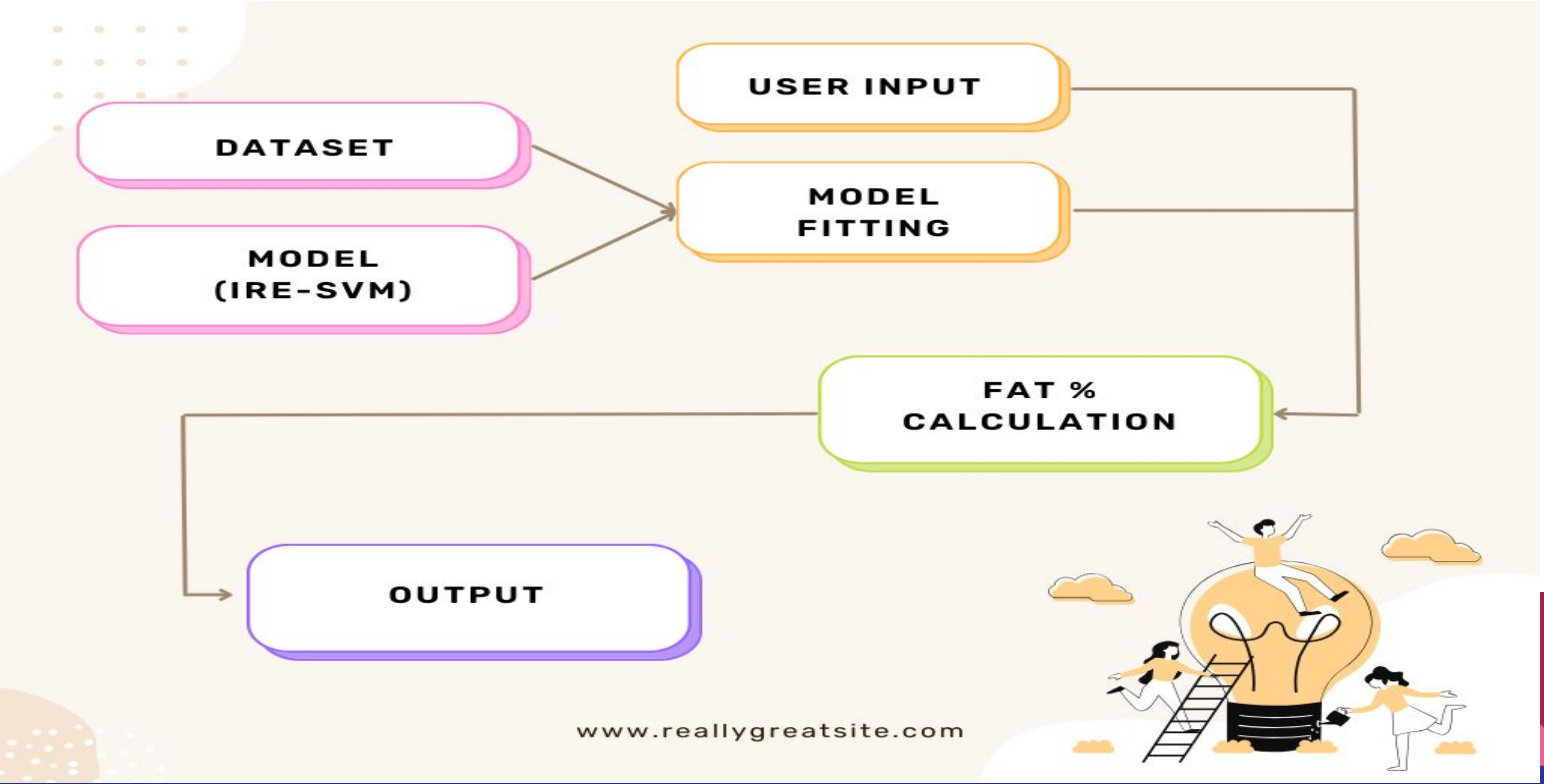

Comparison of Regression Metrics (MSE and MAE)
MAE
MSE
Error Value
0
10
20
30
40
50
IRE-SVM
SVR
MLP_Regression

User Interface

- Interactive Inputs: Implement interactive input fields using JavaScript to allow users to input anthropometric measurements such as age, weight, height, and body part measurements conveniently.
- Real-time Prediction: Utilize JavaScript to enable real-time prediction of body fat percentage based on the entered inputs, leveraging the trained IRE-SVM model.



Building the interface



Future Works

- Recommendations for Future Research:
    a. Future investigations could delve deeper into refining the Improved Relative Error SVM model by exploring additional feature engineering techniques or alternative algorithms.
    b. Further validation studies across diverse datasets and demographic groups would strengthen the generalizability and robustness of the model.
- Practical Applications:
    a. The deployment of the Improved Relative Error SVM model in clinical settings holds promise for facilitating personalized healthcare interventions.
    b. Its ability to provide accurate body fat predictions can inform tailored treatment strategies and risk assessment protocols for obesity-related conditions.

Conclusion

-Our study introduces the Improved Relative Error Support Vector Machine (IRE-SVM) for body fat prediction, showcasing its superiority over three comparative algorithms.

-While maintaining consistently high performance across various metrics, IRE-SVM's slight deviation in Mean Absolute Error (MAE) from one model is negligible in light of its overall effectiveness

-Ultimately, IRE-SVM offers a robust tool for personalized healthcare interventions in obesity management and disease prevention.

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THANK YOU