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An Innovative Deep Neural Network Model for Precise Calorie Burn Prediction from Physical Activity Data

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ABSTRACTS

Accurate prediction of calories burned during physical activities is crucial for various applications in health monitoring, fitness tracking, and personalized nutrition. Traditional methods often lack the precision needed for individualized estimates, which has increased interest in advanced machine learning approaches. This research introduces a deep learning model designed to predict calories burned with enhanced accuracy by capturing complex, non-linear relationships in the data. The model employs a multilayer perceptron neural network, Leaky ReLU activations, dropout regularization, and the Adam optimizer to improve generalizability and prevent overfitting. The evaluation of training and validation loss over epochs demonstrated the model's robustness and capacity to generalize effectively to novel data. The model's performance was evaluated using various metrics, achieving superior results with a remarkable Mean Absolute Error (MAE) of 0.27% and an accuracy of 99.73%, outperforming other models discussed in the literature. These findings indicate that deep learning offers significant potential for improving calorie prediction models, providing more reliable fitness and health management tools.

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1. INTRODUCTION

In various fields, it is extremely important to predict how many calories are burned during physical activity, including health monitoring, fitness tracking, and personalized nutrition (Anikwe et al., 2022). Accurate calorie prediction models help individuals manage weight, optimize workouts, and maintain a balanced diet (Sebastian et al., 2024). Traditional methods often rely on generic formulas or basic statistical models, which may lack precision and adaptability to individual differences (Mohammed & Ahmed, 2024). Consequently, there is an increasing demand for more sophisticated models that can provide accurate and personalized estimates of energy expenditure (Thompson, 2022).

Innovations, in machine learning have opened up possibilities for improving the accuracy of calorie estimation models. Strategies like linear regression, logistic regression, and ensemble methods like XGBoost have demonstrated the potential to enhance prediction accuracy (Kumar & Garg, 2018). However, these approaches often struggle with complex, non-linear relationships and may not fully capture the intricate patterns in the data, especially when dealing with diverse user profiles and varying exercise intensities (Molchanov et al., 2022).

To overcome these challenges, this study explores applying deep learning techniques for calorie prediction. Deep learning models are particularly well-suited for capturing complex dependencies between input features (Zebari et al., 2024). In this study, we've developed a deep neural network model incorporating layers, dropout regularization, and advanced activation functions to improve predictive accuracy and generalizability. Our main goal is to establish a deep learning model for predicting calories burned and assess its performance using metrics like MAE, accuracy, precision, recall, and F1 score. We also compare our model with existing methods to highlight its strengths and areas that could be enhanced. By integrating techniques like Leaky ReLU activations, dropout regularization, and the Adam optimizer, this model aims to advance the field of calorie prediction.

Several studies have focused on improving calorie prediction accuracy using machine learning techniques. These studies highlight the ongoing efforts in the field, which our work builds upon by exploring the potential of deep learning.

(Sheng, Embi, & Hashim, 2024) examined different machine learning models to predict calories burned when exercising, including LightGBM Regression, XGBoost Regression, Random Forest Regression, Ridge Regression, Linear Regression, Lasso Regression, and Logistic Regression. They identified LightGBM as the most accurate model, with an MAE of 1.27%. Their findings suggest that LightGBM's reliability makes it an ideal choice for integration into fitness recommender systems, helping users achieve their fitness goals and enhancing the effectiveness of fitness tracking technologies.

(Nipas et al., 2022) presented an analysis of Linear Regression, Ridge Regression, and Random Forest Regression for predicting calories burned when exercising. Their study involved data preparation, cleaning, analysis, and model training using K-fold validation. In the testing, the random forest model had the highest MAE of 1.81%. Based on the results, the random forest model can accurately predict calorie burn due to its ability to capture complex data patterns.

(Panwar, Bhutani, & Saini, 2023) explored the prediction of calories burned using various regression algorithms, including Linear Regression, XGBoost Regression, AdaBoost Regression, Decision Tree Regression, Random Forest, and SVM. According to the researchers, calorie expenditure is affected by factors such as gender, age, weight, height, exercise duration, body temperature, and heart rate. Among the algorithms tested, XGBoost Regression provided the most accurate results, with an MAE of 1.48%, indicating low prediction errors. This suggests that XGBoost is an optimal algorithm for predicting calories burned during exercise.

(Challagundla et al., 2024) presented an approach that utilized multiple machine learning models to precisely estimate the calories burned while exercising. The study tested various machine learning models, which were selected for this study based on their regression performance, including AdaBoost, Random Forest, Gradient Boosting, and Neural Networks. The neural network model demonstrated superior performance, achieving an MAE of 0.54%, outperforming other models. Data preprocessing involved handling missing values and feature selection. Data visualization techniques were also employed to better understand the relationships between variables and the burned calories. According to the study, the neural network is an effective method for developing user-friendly applications for calorie monitoring.

(Aziz et al., 2023) conducted a study on calorie burn prediction utilizing machine learning algorithms, including XGBoost, SVM, linear regression, and random forest. They predicted calories burned during physical activity based on features like heart rate, body temperature, and activity duration. Using 15,000 records with seven features, the XGBoost model attained an accuracy rate of 99.67% and the smallest MAE recorded was 1.48%. This study adds to the field of personal health coaching and monitoring wellness, advancing the field of health and fitness applications.

(Joseph & Vinoy, 2022) produced a study to assess the effectiveness of XGBoost Regressor and Linear Regression models in estimating calories burned during physical activity. The dataset contained attributes such as workout time, age, gender, body temperature, and heart rate. Their investigation found that the XGBoost Regressor beat the Linear Regression model, with an MAE of 2.71% versus Linear Regression's MAE of 8.38%. These findings show that the XGBoost Regressor makes more accurate predictions, making it a better alternative for fitness tracking and calorie control systems.

The literature reviewed highlights significant advancements in calorie prediction using machine learning, with various studies exploring models like XGBoost, linear regression, and random forest. However, a common limitation across these studies is their reliance on traditional machine learning algorithms, which may struggle with capturing complex, non-linear relationships within the data. Most studies reported MAE values that reflect decent but not optimal

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accuracy. While these studies concentrate on machine learning, my research uses deep neural network methods that could identify more complex patterns and relationships, to decrease prediction errors and increase the model's generalizability.

This study made the following main contributions:

- Developed a deep learning model through a multilayer perceptron neural network having Leaky ReLU activations and dropout regularization for the effective capture of complex data patterns and prevention of overfitting.
- Compiled the model with an Adam optimizer and binary cross-entropy loss, with early stopping added to prevent overfitting and enhance the model's generalization ability.
- Visualized the training and validation loss over epochs, enabling insights into the model's learning process and the effectiveness of early stopping.
- Outperformed the state-of-the-art approaches reported in the literature across various metrics, demonstrating its effectiveness and superiority in the prediction task.

This paper is structured in this manner; In Section 2 we describe the methodology of the model we propose. Section 3 shows the results of our experiments. Offers a comparison of our models, with those reported in the literature. Finally, Section 4 provides a summary of our contributions. Offers insights, for future research paths.

2. METHODOLOGY

The methodology implemented in the proposed model is shown in Fig. 1, where each stage of the process is explained in detail in the following subsections.

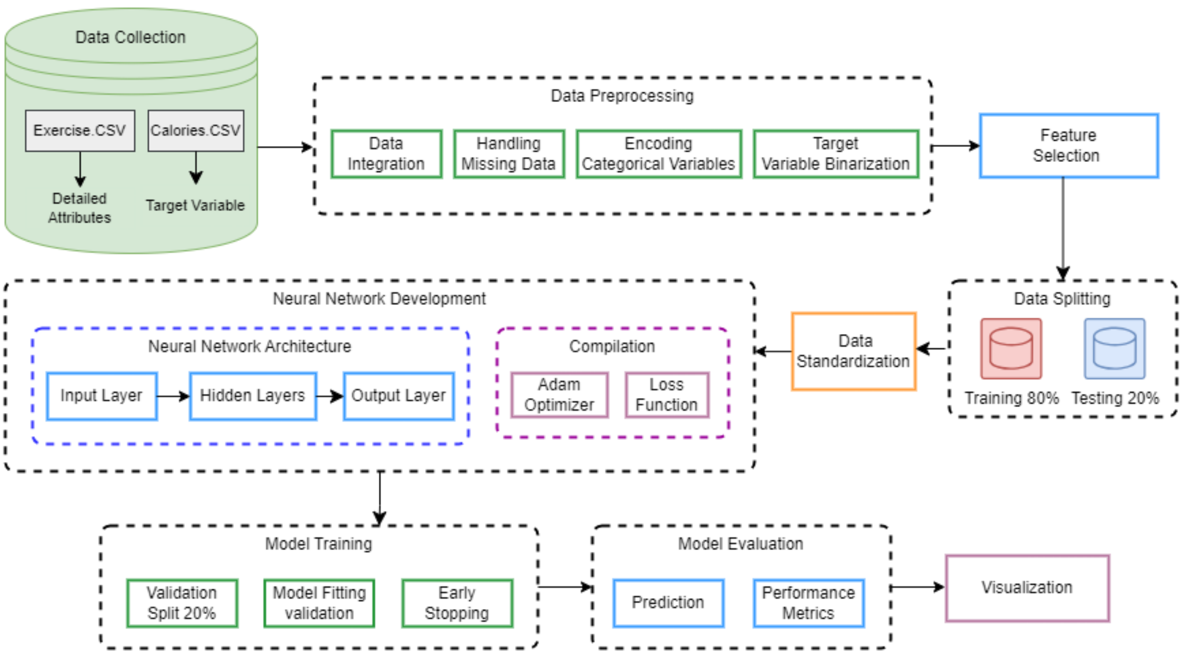

Fig. 1. Architecture of the proposed model

2.1. Data Collection

The dataset utilized in this research was sourced from the Kaggle repository. It consists of two files, "exercise.csv" and "calories.csv", comprising 15,000 instances and seven attributes. The file "exercise.csv" includes detailed attributes for each individual, such as gender, age, workout duration, heart rate, body temperature, height, and weight. This data serves as the training input. The file "calories.csv" contains the target variable, representing the calories burned by the corresponding individuals.

2.2. Data Preprocessing

- Data Integration: The two datasets were combined based on their common attributes, creating a unified dataset containing exercise details and corresponding calorie values.
- Handling Missing Data: The combined dataset was examined for missing values using the .isnull().sum() function. Any missing values would be addressed, although in this case, the dataset did not contain any.
- Encoding Categorical Variables: The 'Gender' column, a categorical variable, was encoded into numerical values where 'male' was mapped to 0 and 'female' to 1.
- Target Variable Binarization: The target variable, 'Calories', was binarized based on its median value. Instances with calorie values above the median were assigned a value of 1, and those below the median were assigned 0. This conversion turned the regression problem into a binary classification task.

2.3. Feature Selection

Feature selection is vital for model accuracy. In this study, the feature set (X) included all columns except user_id and calories. user_id was excluded as it has no predictive value, and 'Calories' served as the target variable (Y), binarized for binary classification. The selected features gender, age, workout duration, heart rate, body temperature, height, and weight, were chosen based on their relevance to calorie expenditure, ensuring the model focused on key attributes for improved accuracy.

2.4. Data Splitting

The dataset was split into training and testing sets using an 80/20 ratio. The train_test_split function from sklearn.model_selection was utilized, ensuring that the model could be evaluated on unseen data.

2.5. Data Standardization

The features were standardized using StandardScaler from sklearn.preprocessing to ensure equal contributions from all features. The scaler was fitted on the training data and then applied to both training and testing datasets.

2.6. Multilayer Perceptron Neural Network Development

The neural network architecture used in this study, as illustrated in Fig. 2, consists of an input layer with 7 units corresponding to the features gender, age, workout duration, heart rate, body temperature, height, and weight. It includes three hidden layers and an output layer. The first hidden layer

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contains 256 neurons followed by a LeakyReLU activation function with an alpha of 0.1 and a dropout rate of 30% to prevent overfitting. The LeakyReLU activation function introduces a small slope (0.1 in this case) for negative values, which helps avoid the issue of dead neurons that can occur with traditional ReLU activations (Mastromichalakis, 2020). Dropout, with a rate of 30%, is a regularization technique used to randomly set a fraction of input units to zero during training, which helps prevent overfitting by encouraging the model to learn more robust features (Jabir & Falih, 2021). The second hidden layer has 128 neurons, also followed by a LeakyReLU activation and a dropout rate of 30%. The third hidden layer includes 64 neurons with a LeakyReLU activation function. The output layer has a single neuron with a sigmoid activation function for binary classification.

The model is compiled using the Adam optimizer, which is an adaptive learning rate optimization algorithm designed to combine the advantages of both the AdaGrad and RMSProp algorithms. Adam adjusts the learning rate of each parameter individually based on estimates of lower-order moments, making it particularly well-suited for problems with sparse gradients and noisy data (Reyad, Sarhan, & Arafa, 2023). The learning rate for Adam in the proposed model was set to 0.001 and is trained with a binary cross-entropy loss function.

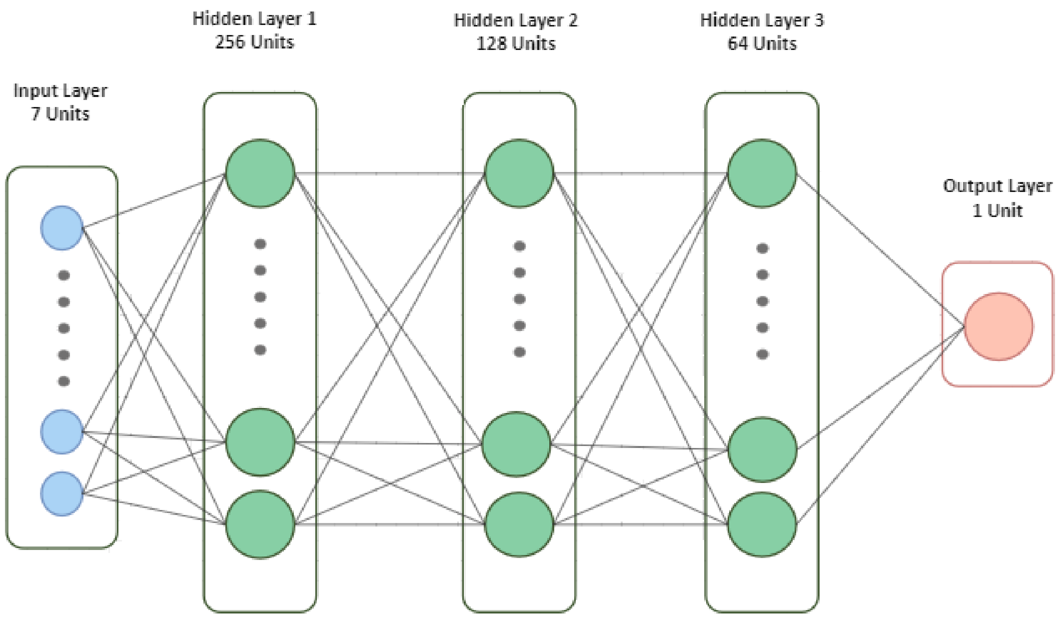

Fig. 2. Architecture of the multilayer perceptron neural network

2.7. Model Training

Early stopping was implemented to prevent overfitting during the model fitting process. The EarlyStopping callback function closely monitored the validation loss throughout training, ensuring that if there were no improvements for 10 consecutive epochs, the training would be halted to avoid overtraining. The model was fitted on the training set for up to 200 epochs, with a validation split of 20% to evaluate performance during training. The early stopping mechanism was crucial in determining the optimal number of epochs, allowing the model to achieve the best possible generalization without overfitting the training data (Thike et al., 2020).

2.8. Model Evaluation

Predictions were made on the testing set using the trained model, with predictions converted into binary outcomes based on a threshold of 0.5. The model's performance was assessed using several performance metrics, including MAE, which gives the mean of the absolute differences between prediction and actual values. MAE is a simple average measure that treats all errors equally and is in the same unit as the target variable, thus very interpretable, where a lower MAE indicates better performance (Hodson, 2022). Accuracy was assessed as the percentage of correct predictions to the total number of predictions as well as the precision which measured the true positive predictions to the total positive predictions. As for the calculation of recall it was done according to the formula true positive predictions divided by actual positive instances. Finally, the F1 Score, the harmonic average of both the precision and the recall, was used to provide a balanced assessment between these two metrics.

2.9. Visualization

The model's loss over the training epochs was plotted to visualize both the training and validation loss, helping to observe the model's learning process and the point at which early stopping occurred. The accuracy over epochs was also tracked, providing insight into how well the model was improving its predictions over time. This dual analysis of loss and accuracy helps identify overfitting, underfitting, and the optimal stopping point for training (Salman & Liu, 2019). Additionally, by analyzing these metrics together, it becomes easier to ensure the model is not only accurate but also generalizes well to new data (Torres et al., 2021).

3. RESULTS AND DISCUSSION

A comprehensive analysis of the proposed model is carried out using commonly used performance measures. This analysis involves evaluating the accuracy and loss trends observed across epochs, providing an understanding of the model's learning process. The overall performance of the model is then discussed, focusing on the main findings. Finally, the effectiveness of the model is compared with existing approaches, highlighting its strengths.

3.1. Accuracy and Loss vs. Epoch

The model's performance was assessed by tracking accuracy and loss metrics over training epochs, revealing its learning behavior. Fig. 3 illustrates the trend of accuracy across the training and validation sets as the number of epochs increased. Initially, the model's accuracy exhibited fluctuations, reflecting its adjustment to the data, but eventually, it stabilized, indicating that the model effectively learned the underlying patterns in the data. In parallel, Fig. 4 presents the loss curves for both the training and validation sets, which decreased over epochs, showing that predictions aligned better with actual outcomes. Early stopping helped prevent overfitting, as the validation loss plateaued after a certain point. This

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suggests the model generalized well to unseen data, avoiding significant overfitting or underfitting. Examining accuracy and loss versus epochs ensures the model not only fits the training data but also performs reliably on the validation set, confirming its robustness.

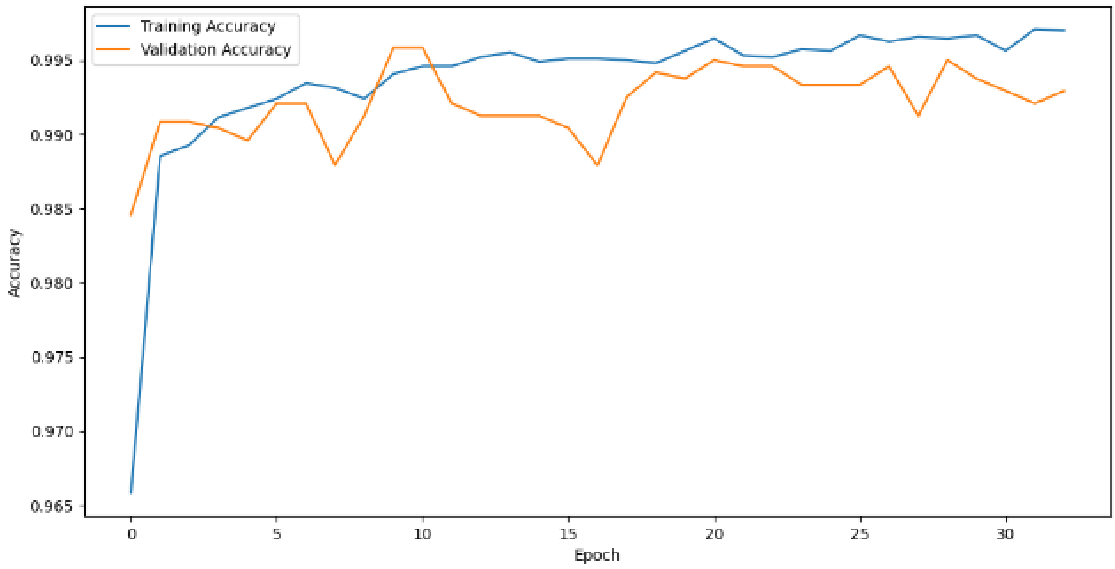

Fig. 3. Accuracy trends over epochs

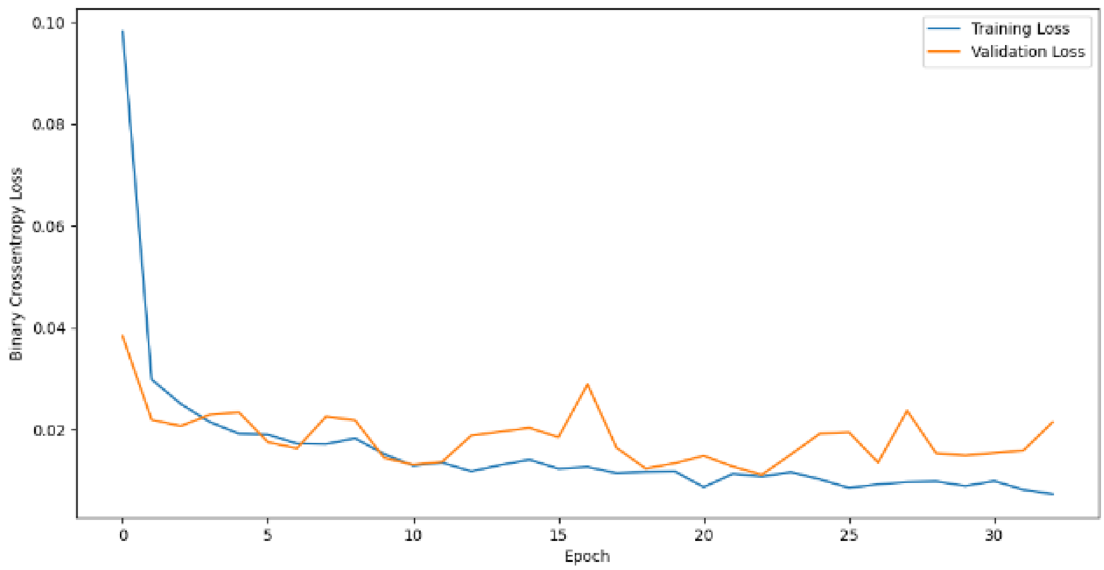

Fig. 4. Loss curves over epochs

3.2. Overall Performance of The Proposed Model

The performance of the proposed model to predict calorie burn was excellent for several assessment metrics. An accuracy of 99.73% was achieved by the model, meaning that it is extremely accurate in its predictions. Precision was documented at 99.60% which indicates the ability to precisely determine true positives and minimal false positives. The recall of 99.87% illustrates that the presented model shows the ability to accurately identify most of the real positive cases. In addition, the F1 Score obtained was 99.73%, which put the model in a good position with an adequate balance between precision and recall thereby confirming the model's reliability. MAE was noticeably very low at 0.27%, this proves the usefulness of the model in determining the exact number of calorie expenditure.

3.3. Comparison with the state-of-art Approaches

The proposed model is compared with the models of calorie burn prediction that have been documented in the literature; all of these models were developed using similar datasets. To guarantee a fair comparison, the proposed model also used these datasets. The aim is to find how the proposed model performs compared to existing models. The results of the literature models utilized in this comparison indicate their best performance as achieved by applying different techniques. MAE and accuracy were used as a measure of performance in the comparison. As demonstrated in Table 1 and Fig. 5, the proposed model outperformed all the compared models in terms of achieving a lower MAE.

Table 1. Comparison between the proposed model and recent models from the literature

Reference	Optimal Method	Accuracy %	MAE %
(Sheng, Embi, & Hashim, 2024)	LightGBM Regression	-	1.27
(Nipas et al., 2022)	Random Forest Regression	95.77	1.81
(Panwar, Bhutani, & Saini, 2023)	XGBoost Regression	-	1.48
(Challagundla et al., 2024)	Neural Network Regression	-	0.54
(Aziz et al., 2023)	XGBoost Regression	99.67	1.48
(Joseph & Vinoy, 2022)	XGBoost Regression	-	2.71
Proposed Model	Multilayer Perceptron Neural Network	99.73	0.27

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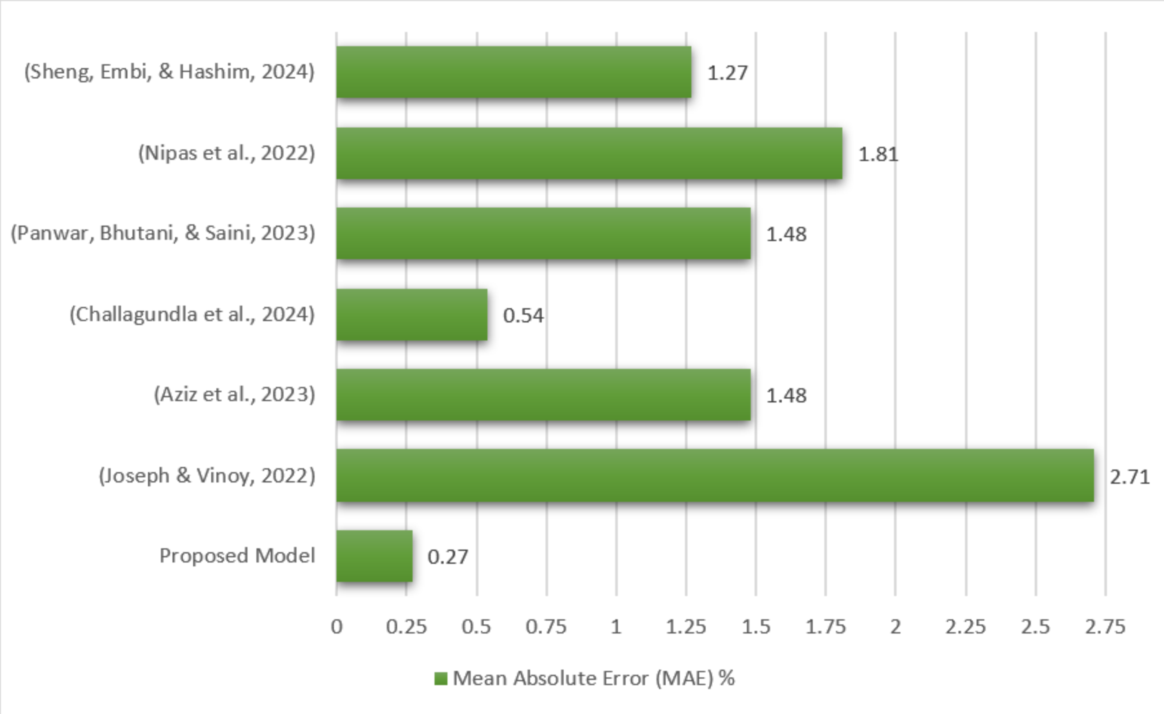

Fig. 5. Comparison of MAE between the proposed model and existing models from the literature.

4. CONCLUSION

In this study, we developed a deep learning model for predicting calories burned during physical activities, leveraging advanced techniques such as Leaky ReLU activations, dropout regularization, and the Adam optimizer. Our results demonstrate that the proposed model significantly outperforms traditional machine learning approaches regarding MAE and accuracy. By effectively capturing complex, non-linear relationships within the data, the model exhibits high generalizability and robustness, as evidenced by its stable performance across the training and validation sets. Evaluating accuracy and loss over epochs provided critical insights into the learning process of the model, ensuring that early stopping was appropriately applied to prevent overfitting. Compared to the state-of-the-art models, our deep learning approach achieved a lower MAE, demonstrating its superiority in calorie prediction.

However, some limitations should be considered despite the positive findings. The dataset was relatively small and specific to certain physical activities, potentially limiting the model's generalizability to other exercises or populations. Additionally, the model focused on common features such as gender, age, and workout duration, without incorporating more granular data like specific activity type, intensity, or environmental factors.

Future work could focus on expanding the dataset, incorporating additional features such as activity type and intensity, and experimenting with other deep learning architectures to enhance the model's predictive capabilities and generalization to diverse populations.

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