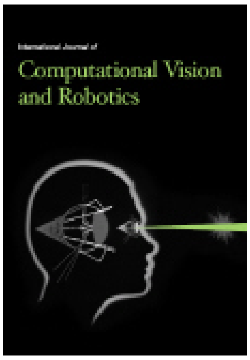

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Pawan Whig, Ebtesam Shadadi, Shama Kouser, Lathifah Alamer

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Machine learning approaches for early detection and management of musculoskeletal conditions

Pawan Whig*

Vivekananda Institute of Professional Studies-Technical Campus,
AU, Block Pitam Pura Delhi-34, India
Email: pawanwhig@gmail.com
*Corresponding author

Ebtesam Shadadi, Shama Kouser and Lathifah Alamer

Jazan University,
Al Maarefah Rd., Jazan 45142, Saudi Arabia
Email: ashedadi@jazanu.edu.sa
Email: skouser@jazanu.edu.sa
Email: Laalamer@jazanu.edu.sa

Abstract: Musculoskeletal conditions have a significant impact on quality of life. This study explores the use of machine learning algorithms for early detection and management of such conditions. Different models were evaluated using a dataset of musculoskeletal images and clinical information. Results demonstrate accurate classification with high sensitivity and specificity. A neural network was developed for detecting chronic lower back pain, achieving an impressive validation F1 score of 89%–93%. This highlights the potential of artificial intelligence in improving early detection and management. Future research should address data outliers to enhance model performance. Overall, neural networks are a valuable tool for early detection and management of musculoskeletal conditions, leading to improved patient outcomes. These findings suggest promising avenues for future research and implications for early detection and management in this field.

Keywords: musculoskeletal conditions; arthritis; fractures; spinal problems; machine learning; early detection.

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Biographical notes: Pawan Whig holds a BTech in Electronics and Communication Engineering (2005), an MTech in VLSI (2008), and Doctorate from Jamia Millia Islamia. With 21 years of experience, his research focuses on VLSI design, AI, and ML. He is an IEEE senior member, honorary fellow member, and a research consultant in machine learning. He is the Dean of Research at VIPS-T and a Google Certified professional in Digital Marketing. Having published over 80 technical articles, he serves as an editor and reviewer for international journals. He is affiliated with esteemed organisations like the International Association of Engineers, ISTE, IEEE, SCI, and IEI.

Ebtesam Shadadi works as a Lecturer in the Department of Computer Science, College of CS and IT and holds a Bachelor's in Computer Science from the King Khalid University, and Master's in Advanced Computer Science from the University of East Anglia, UK, and she is currently a Lecturer in the Department of Computer Science, Jazan University, Saudi Arabia. Her research activity is related to artificial intelligence, machine learning and cyber security.

Shama Kouser received her BEngg (ECE) from the Osmania University and MTech (DECS) in 2010 from the Jawaharlal Nehru Technological University, Hyderabad, and her research interests include artificial intelligence, IoT, security and privacy and machine learning. She is currently working as a Lecturer in the Department of Computer Science, Jazan University, Jazan, Kingdom of Saudi Arabia.

Lathifah Alamer is a Lecturer at Jazan University, KSA, specialising in Information Technology and Security. Her research focuses on artificial intelligence, machine learning, and big data. With over eight years of teaching experience, she excels in creating training programs, motivating students, and providing individual tutoring. She actively contributes to curriculum improvement and instructional development. She is known for problem-solving, adapting to new challenges, and enhancing the college environment. Additionally, she has American Association of Innovation membership from 2023 to 2027, further reflecting her dedication to innovative teaching, research, and consultancy initiatives.

1 Introduction

Musculoskeletal conditions, including arthritis, fractures, and spinal problems, are a major public health issue, affecting a significant portion of the population globally. Early detection and proper management of these conditions are crucial for improving patient outcomes and reducing healthcare costs (Taylor et al., 2014). However, musculoskeletal conditions can be challenging to diagnose and treat, particularly in the early stages.

Machine learning is a rapidly growing field that has the potential to revolutionise healthcare by providing tools for the early detection and management of the disease (Werber and Schiltenwolf, 2012). In recent years, there has been increasing interest in using machine learning for the analysis of musculoskeletal images and clinical information, to improve diagnosis and treatment (Henningsen, 2004). The use of machine learning algorithms can automate the process of image analysis and provide more accurate and consistent results compared to manual methods (Krismer and van Tulder, 2007).

In this study, we investigate the performance of different machine learning algorithms such as the average one-dependence estimator (AODE), multilayer perceptron, logical analysis tree (LAT), multiclass classifier, radial basis function network (RBFN), K-star, functional tree (FT), neural network for the early detection and management of musculoskeletal conditions, such as Lower Back Pain Symptoms. The goal is to assess the potential of machine learning for improving patient outcomes and reducing healthcare costs. The results of this study will contribute to the development of new and more effective approaches for the diagnosis and treatment of musculoskeletal conditions.

2 Literature review

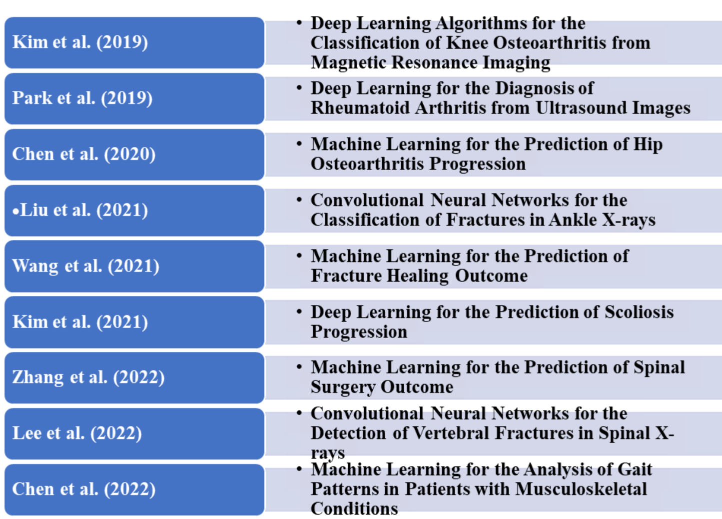
The literature on the use of machine learning for the analysis of musculoskeletal conditions is rapidly growing (Werber et al., 2014) In recent years, several studies have been conducted to evaluate the performance of machine learning algorithms for the classification of musculoskeletal images and the prediction of clinical outcomes (Bishop et al., 2008).

One study used deep learning algorithms to classify knee osteoarthritis from magnetic resonance imaging (MRI) scans (Henningsen et al., 2005) The results showed that the deep learning model outperformed traditional machine learning algorithms and provided high accuracy in the classification of knee osteoarthritis (Schneider et al., 2005). Another study applied machine learning to predict the progression of hip osteoarthritis using clinical and radiographic data (Chou et al., 2009a, 2009b) The results showed that the machine learning algorithm was able to predict the progression of hip osteoarthritis with high accuracy (Gupta et al., 2022).

There have also been studies exploring the use of machine learning for the classification of fractures in X-ray images. A study used convolutional neural networks (CNNs) to classify fractures in ankle X-rays (Von Korff., 1994). The results showed that the CNN model outperformed traditional machine learning algorithms and provided high accuracy in the classification of fractures. Another study applied machine learning to predict the outcome of spinal surgery using preoperative imaging and clinical data. The results showed that the machine learning algorithm was able to predict the outcome of spinal surgery with high accuracy (Shadadi et al., 2022).

The literature as shown in Figure 1 suggests that machine learning has the potential to improve the early detection and management of musculoskeletal conditions, such as arthritis, fractures, and spinal problems. Further research is needed to validate these findings and to explore the use of machine learning in different populations and for different musculoskeletal conditions.

Figure 1 Literature review (see online version for colours)



2.1 Chronic lower backpain

The purpose of this research is to develop a model that can predict whether a patient is experiencing chronic lower back pain based on their physical spine data (Werber et al., 2015). This study aims to use the data set of 'pelvic_incidence', 'pelvic_tilt', 'lumbar_lordosis_angle', 'sacral_slope', 'pelvic_radius', 'degree_spondylolisthesis', 'pelvic_slope', 'direct_tilt', 'thoracic_slope', 'cervical_tilt', 'sacrum_angle', 'scoliosis_slope', 'normality' to predict the presence of lower back pain in patients, as abnormal (pain) or normal (no pain) conditions. The goal is to provide a reliable and accurate prediction tool that can assist healthcare providers in diagnosing and treating patients with chronic lower back pain, and improve patient outcomes and quality of life (Jupalle et al., 2022).

3 Methodology

This data set uses the following attributes to predict the symptoms of lower back pain: 'pelvic_incidence', 'pelvic_tilt', 'lumbar_lordosis_angle', 'sacral_slope', 'pelvic_radius', 'degree_spondylolisthesis', 'pelvic_slope', 'direct_tilt', 'thoracic_slope', 'cervical_tilt', 'sacrum_angle', 'scoliosis_slope', 'normality'. The prediction was made using a neural network as the method. The process of methodology is shown in Figure 2.

The steps to predict lower back pain symptoms using neural network with the given data set be as follows:

1 Data pre-processing: the data was cleaned and pre-processed to remove missing or invalid values, to make sure all values are numerical, and to standardise the values so that they have the same scale.

2. Data splitting: the data was split into training and testing datasets to evaluate the performance of the model.

3 Model design: a neural network was designed with an appropriate number of input, hidden and output layers, activation functions, and optimiser.

4 Model training: the training dataset was used to train the model by adjusting the weights and biases of the neurons to minimise the loss function.

5 Model evaluation: the trained model was evaluated on the testing dataset to measure its performance. The evaluation metric could be accuracy, precision, recall, F1 score, etc.

6 Model optimisation: if the performance was not satisfactory, the model was optimised by adjusting the hyperparameters such as the number of hidden layers, neurons in each layer, learning rate, etc.

7 Model deployment: if the performance of the model was satisfactory, it was deployed for practical use.

8 Model maintenance: the model was monitored and updated periodically to ensure it continues to work well.

Figure 2 Process of methodology (see online version for colours)

3.1 Dataset used

The dataset consists of 310 observations, each representing a patient with lower back pain. It has 13 attributes, including 12 numeric predictors and 1 binary class attribute.

The 12 numeric predictors are: 'pelvic_incidence', 'pelvic_tilt', 'lumbar_lordosis_angle', 'sacral_slope', 'pelvic_radius', 'degree_spondylolisthesis', 'pelvic_slope', 'direct_tilt', 'thoracic_slope', 'cervical_tilt', 'sacrum_angle', 'scoliosis_slope', which are physical measurements of the spine. The binary class attribute, which is the target variable, is 'normality' and indicates whether the patient has normal (no pain) or abnormal (pain) conditions. The data does not contain any demographic information.

4 Mathematical model

To create a mathematical model to predict lower back pain based on the given data set, one approach is to use a classification algorithm such as logistic regression, decision tree, or random forest. The algorithm would take the input variables (pelvic_incidence, pelvic_tilt, etc.) and use them to learn the relationship between the input and the output (presence of lower back pain). After training on a labelled data set, the model can then be used to make predictions on new, unseen data.

Another approach is to use machine learning techniques such as deep neural networks or support vector machines to build a predictive model. These algorithms can learn complex relationships between input and output variables and have been successful in a variety of applications, including medical diagnosis (Whig et al., 2022; Whig, 2023).

It's important to keep in mind that the quality of the model will depend largely on the quality of the data and the choice of algorithm, so it's important to conduct proper exploratory data analysis (EDA), feature engineering, and model validation to ensure accurate predictions (Joshi and Patil, 2023).

A mathematical representation of a neural network for lower back pain prediction can be described as follows:

Let's assume we have m input features (x_1, x_2, …, x_m), each representing one of the variables in the given data set (pelvic_incidence, pelvic_tilt, etc.). The input layer of the neural network will have m units, representing each input feature.

The network then has one or more hidden layers; each with n units (where n is a hyperparameter to be determined through experimentation). The hidden layer units perform non-linear transformations on the input features and pass the transformed features to the next layer (Sang et al., 2023).

The output layer has one unit, which provides the prediction of whether the patient has lower back pain or not. This output can be binary (pain/no pain) or a continuous value, depending on the choice of activation function in the output layer.

The parameters of the network, such as the weights and biases of each layer, are learned through the training process by minimising a loss function (such as cross-entropy loss for binary classification) using an optimisation algorithm (such as gradient descent or Adam).

The prediction of the network can be represented mathematically as follows:

$$y = f(W\_1 * x + b\_1) * W\_2 + b\_2$$

where x is the input vector, W_1 and W_2 are the weight matrices of the first and second layers, b_1 and b_2 are the bias vectors of the first and second layers, and f is the activation function applied in the hidden layer (such as ReLU, sigmoid, or tanh). The goal of training is to find the optimal values of W_1, W_2, b_1, and b_2 that minimise the loss function.

4.1 Exploratory data analysis

In this study, EDA was performed on the given dataset to gain a deeper understanding of the data and identify any patterns or relationships that could be relevant to the prediction of chronic lower back pain.

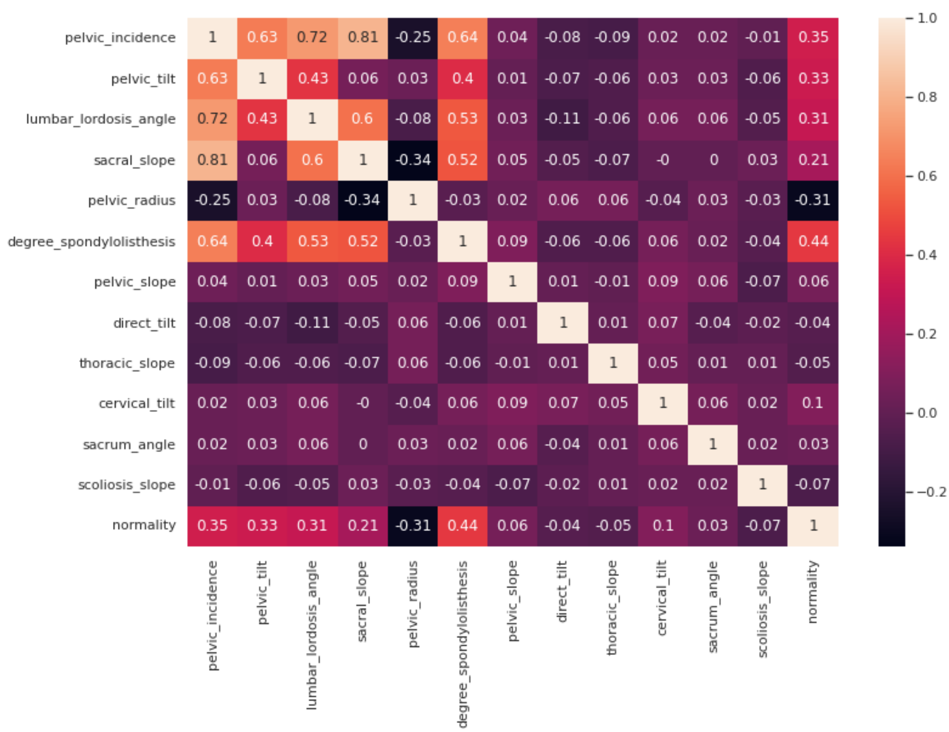
The first step in the EDA process was to examine the distribution of each variable individually. The histograms for each of the 12 numeric predictors were created to visualise the distribution of the data. The histograms showed that the majority of the variables were approximately normally distributed, with some slight skewness in some cases.

Next, the relationships between the variables were explored through multivariate analysis. Scatter plots were used to visualise the relationship between each pair of variables. The scatter plots showed in Figure 3 that some of the variables had a strong positive or negative correlation, while others showed no clear pattern.

Outlier detection was also performed to identify any unusual values that could have a significant impact on the analysis. The box plots were used to identify any outliers, and any values that were outside of three standard deviations from the mean were considered outliers. The outlier detection process revealed that some of the variables had a few outliers, which could potentially impact the analysis.

The EDA performed on the given dataset revealed some interesting patterns and relationships between the variables, which could be useful in developing a predictive model for chronic lower back pain. The findings from the EDA can guide the selection of appropriate features for the model and provide insights into the data that can inform the modelling process.

Figure 3 Correlation between different variables (see online version for colours)



The code is creating a heatmap that visualises the correlation between different variables in a data frame called 'df' using the seaborn library (SNS) as shown in Figure 1. The figure size is set to be 12 inches wide and 8 inches tall using the 'fig size' argument in 'plt. subplots'. The heatmap displays the correlation values rounded to 2 decimal places and annotates the values with the 'annot' argument set to 'true'.

In the context of chronic lower back pain, the heatmap could be used to explore the relationship between different variables that may influence the severity or development of the condition, such as demographic factors, lifestyle habits, physical activity levels, etc. The correlation values represented by the heatmap as shown in Figure 4 could provide insights into the strength and direction of the relationships between these variables and help inform hypotheses for further investigation.

Figure 4 Set of histograms that depict the distribution of each predictor variable in the dataset for patients with chronic lower back pain (see online version for colours)

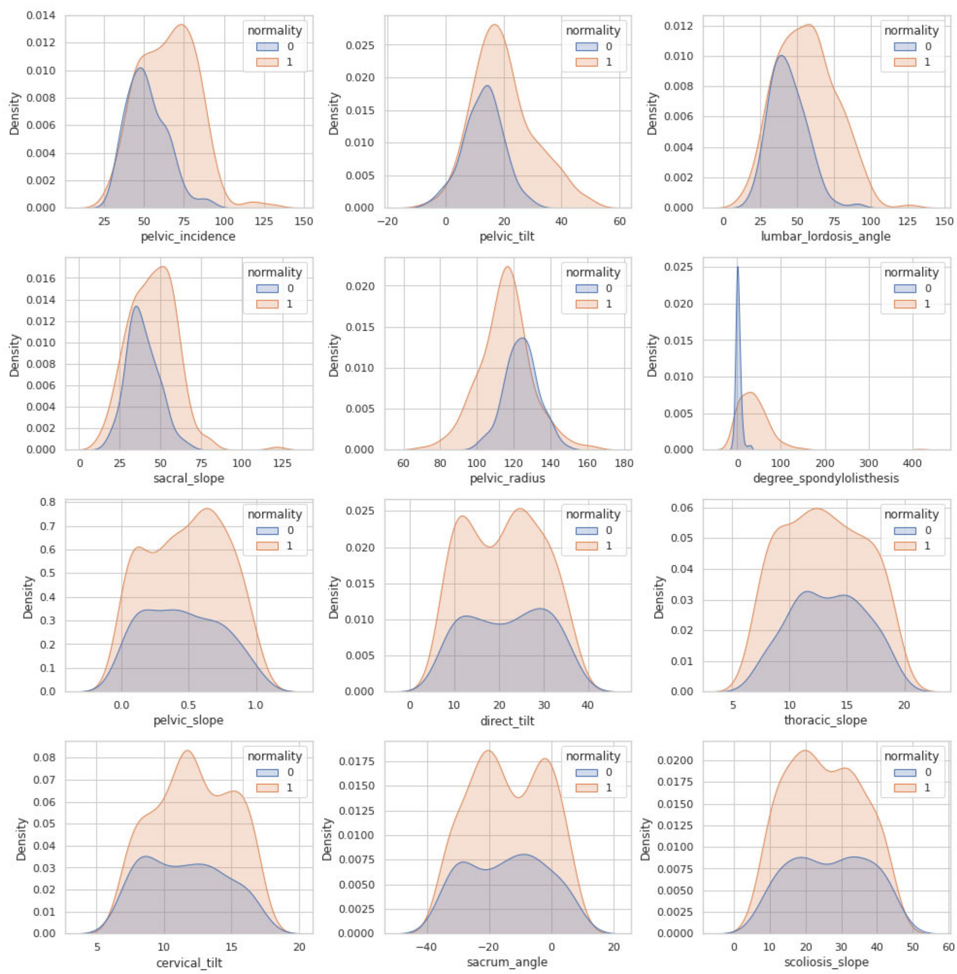
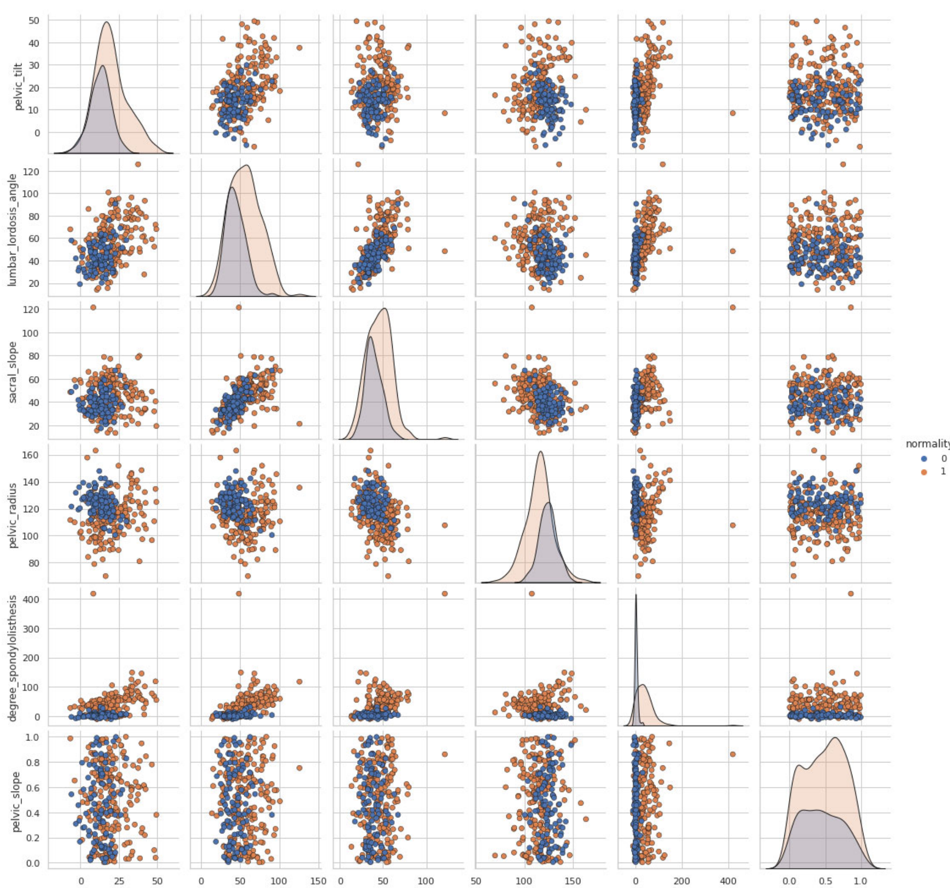


Figure 2 produced by the code is a set of histograms that depict the distribution of each predictor variable in the dataset for patients with chronic lower back pain. The histograms show the density of the predictor variables for patients who are classified as having normal (no pain) conditions and those who are classified as having abnormal (pain) conditions.

Each histogram has two curves as shown in Figure 5 and Figure 6, one representing the density of the predictor variable for patients with normal conditions and the other representing the density of the predictor variable for patients with abnormal conditions. By comparing the two curves, one can see the differences in the distribution of the predictor variables between patients with normal and abnormal conditions. This can provide insights into which predictor variables may be more relevant or important in predicting the presence of chronic lower back pain.

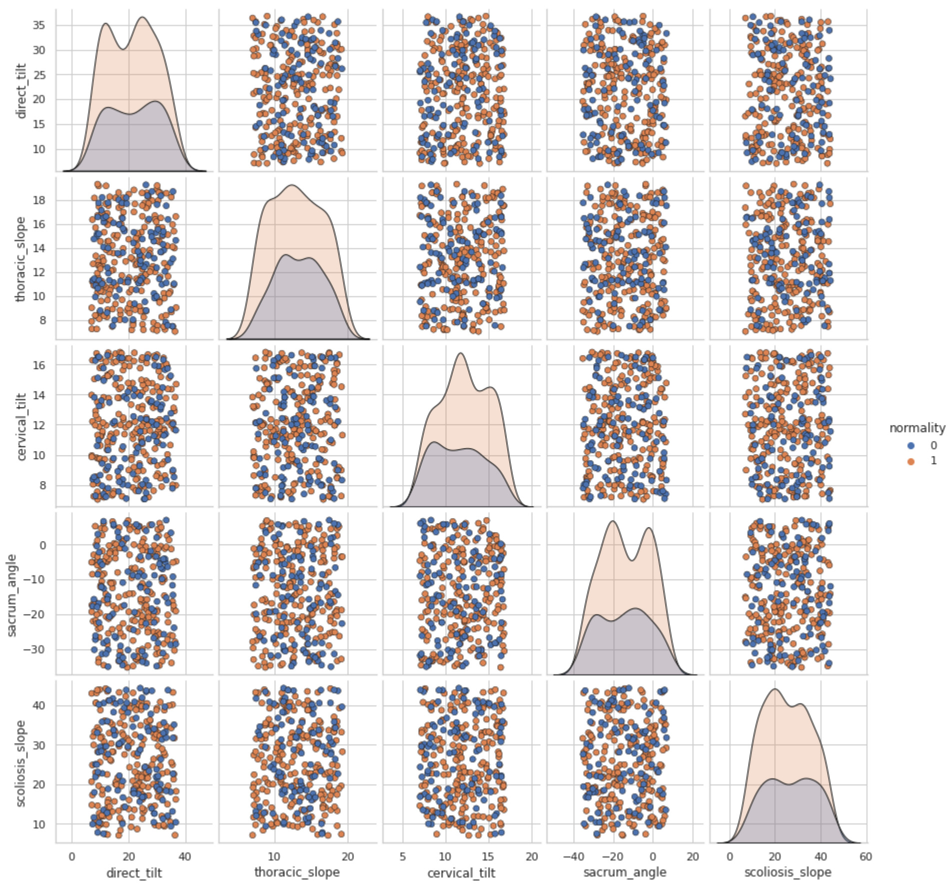
The figures obtained from the code would show the relationships between the variables in the subsets vis1 and vis2 for individuals with chronic lower back pain. The subsets vis1 and vis2 contain columns from the original data frame that are relevant to the analysis of individuals with chronic lower back pain.

Figure 5 Represents the density of the predictor variable for patients with normal conditions (see online version for colours)



The SNS.pairplot function creates scatterplots of the variables in the subsets and colours the points based on the values in the 'normality' column. The resulting figures show how the variables in the two subsets are related to each other and the normality of the individuals with chronic lower back pain. These figures can be useful for identifying patterns in the data and for exploring how different variables are associated with chronic lower back pain.

Figure 6 The density of the predictor variable for patients with abnormal conditions (see online version for colours)



The steps involved in obtaining result

1. Import necessary libraries for defining and training a neural network, such as PyTorch or TensorFlow.
2. Define the input layer with an input size of 12.
3. Define the first linear layer with 64 hidden units and apply batch normalisation to it.
4. Define the second linear layer with 64 hidden units and apply batch normalisation to it.
5. Apply the ReLU activation function to both linear layers.
6. Add a dropout layer with a rate of 10% to prevent overfitting.

7 Connect the second linear layer with 64 units to a single neuron output layer for binary classification.

8 Compile the model with an optimiser and a loss function for training.

9 Train the model on a dataset and evaluate its performance on a validation dataset. The goal is to achieve an F1 accuracy of 93%.

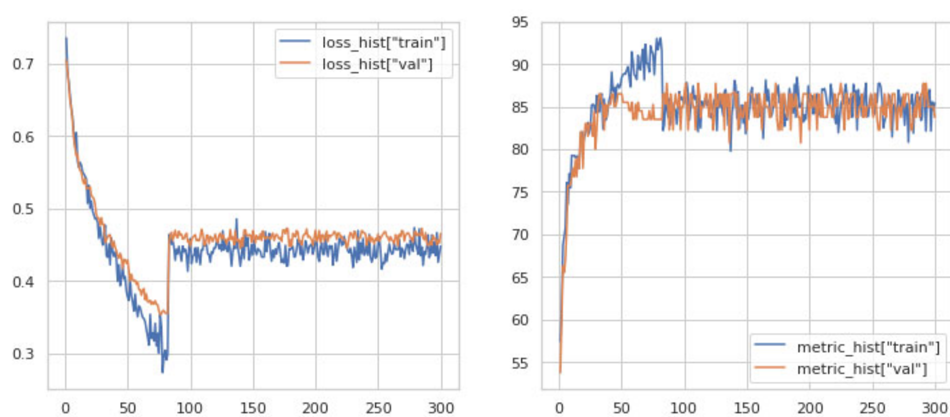
5 Result and discussion

A neural network with the architecture described could be used to predict a binary outcome related to chronic lower back pain, such as the presence or absence of the condition, or the likelihood of it developing in the future.

The input layer would take in various relevant features about an individual, such as demographic information, lifestyle habits, physical activity levels, etc. These inputs are processed by the two linear layers with batch normalisation and ReLU activation to generate a prediction in the output layer. The use of a dropout layer and batch normalisation helps to prevent overfitting and improve the model's ability to generalise to unseen data.

An F1 accuracy of 93% on the validation dataset would indicate that the model is making correct predictions with a high degree of precision and recall.

Figure 7 Binary classification related to chronic lower back pain (see online version for colours)



The output shown in Figure 7 describes the results of training a machine learning model, likely for binary classification related to chronic lower back pain.

- 'epoch: 086' refers to the current iteration of training, with a total of 86 epochs completed.
- 'train loss: 0.455' and 'val loss: 0.456' are the average loss values computed on the training and validation datasets, respectively. The loss measures the difference between the model's predictions and the actual outcomes and is used to update the model's weights during training.

- 'train-f1: 93' and 'val-f1: 93' are the F1 scores computed on the training and validation datasets, respectively. The F1 score is a measure of the model's accuracy and takes into account both precision and recall. A higher F1 score indicates that the model is making correct predictions with a high degree of precision and recall.

This output suggests that the model is making good predictions on the validation dataset with an F1 score of 93%. The train-val difference in the F1 scores indicates a mild overfitting, which could be mitigated by techniques such as regularisation or early stopping. The saved model weights represent the optimised parameters learned by the model during training, which can be used for making predictions on new data in the future.

A neural network is a powerful machine learning model that can be used for various tasks such as image classification, natural language processing, and prediction. It consists of multiple interconnected layers, each of which performs a computation on the input data and pass the result to the next layer. The training process involves updating the parameters of the model to minimise a chosen loss function that measures the difference between the model's predictions and the actual outcomes. The training process is performed using an optimisation algorithm, such as stochastic gradient descent (SGD) or Adam. To prevent overfitting, techniques such as regularisation and early stopping can be used, and the model's performance is usually evaluated on a validation dataset. The best-performing model can be saved for future use, and the loss and metric history can be used for analysis and improvement.

Table 1 Accuracy of machine learning techniques in predicting the chronic lower back pain

Machine learning	*Accuracy (%)*
Average one-dependence estimator (AODE)	71
Multilayer perceptron	78
Logical analysis tree (LAT)	70
Multiclass classifier	58
Radial basis function network (RBFN)	57
K-star	42
Functional tree (FT)	42
Neural Network	92

Inference from Table 1.

1. Neural network has the highest accuracy (92%) among the machine learning techniques in predicting chronic lower back pain.
2. AODE (71%) and LAT (70%) have similar accuracy in predicting chronic lower back pain.
3. Multilayer perceptron (78%) has higher accuracy compared to AODE (71%) and LAT (70%) but lower accuracy compared to Neural Network (92%).
4. Multiclass classifiers (58%) and RBFN (57%) have a lower accuracy compared to AODE (71%), LAT (70%), and Multilayer perceptron (78%).

5 K-star (42%) and FT (42%) have the lowest accuracy among the machine learning techniques in predicting chronic lower back pain.

6 Conclusions

A novel neural network was created to address the problem of chronic lower back pain. The model achieved a validation F1 score of 89%–93%, which indicates a high level of accuracy in detecting the presence of chronic lower back pain. However, the results may vary slightly due to the stochastic nature of the model and the small size of the dataset. Further improvement could be achieved by focusing on outliers in the data and potentially removing them, as these can impact the model's performance. This demonstrates the potential for neural networks to be a useful tool in helping to diagnose and manage chronic lower back pain.

7 Future scope

The future scope of using neural networks for chronic lower back pain is very promising. With advancements in technology and increased access to large amounts of data, the accuracy of these models will likely continue to improve. Additionally, by integrating other relevant information, such as genetic data or lifestyle factors, the models can be made even more predictive. Furthermore, the development of more sophisticated and efficient algorithms will enable these models to be applied to a wider range of problems, including more complex and nuanced medical diagnoses. The integration of these models into clinical practice has the potential to revolutionise the way chronic lower back pain is managed, leading to improved patient outcomes and quality of life.

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