Enhancing Dorsalgia Prediction using Neutrosophic Sets in a Genetic Algorithm-Optimized Hybrid CNN-LSTM Framework on Spinal Geometry Parameters

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Abstract

Predicting dorsalgia involves a multifaceted approach that encompasses the analysis of demographic, lifestyle, and medical data. Machine learning algorithms and advanced data analytics play a pivotal role in forecasting the risk of developing back pain. Early prediction aids in proactive interventions and personalized healthcare strategies, thereby mitigating the burden of dorsalgia on individuals and healthcare systems. The proposed feature selection is the initial feature set's most educational elements by evolutionary gravitational search-based feature selection (EGSFS). Specifically, the framework is trained and fine-tuned using spinal geometry parameters, enabling precise identification of individuals at risk of developing dorsalgia. This study presents a novel approach for classification tasks using a Genetic Algorithm (GA)-optimized hybrid Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) model. The GA optimizes the model's architecture and hyperparameters to enhance its performance. The framework is implemented using Python. In the categorization procedure, the Single Neutrosophic sets aid in capturing ambiguity, which is particularly beneficial when handling dorsalgia disorders that may present with confusing symptoms, thus enhancing the accuracy of classifying various dorsalgia conditions. Experimental results demonstrate that this hybrid approach significantly improves classification accuracy, making it a viable option for several practical applications. Experimental results exhibit remarkable improvements in accuracy and predictive power, underscoring the potential of this innovative approach in advancing preventative and personalized healthcare strategies for back pain management. The experiment was built on the lower back pain symptoms dataset. A comparison is made between the experimental results and previous prediction models like Logistic Regression, Decision Tree Classifier, Random Forest, and Support Vector Machine in terms of accuracy, F1-score, precision, and recall. The accuracy of normal and abnormal data is 99%.

Keywords: Dorsalgia; Evolutionary Gravitational Search-Based Feature Selection; Genetic Algorithm; Convolutional Neural Network, Long Short-Term Memory; Machine learning; Single Neutrosophic Sets.

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1 Introduction

People of all ages can have back pain, a general term encompassing pain in the cervical spine, dorsal spine, and lower spine.[1] The interaction between spine position and motion leads to cervicothoracic dorsalgia, a posteriorly localized pain in the cervicothoracic spine area. Cervicothoracic dorsalgia can arise from a variety of contributory circumstances.[2] Because it is so common, discomfort in the back is one of the most important medical issues. Back pain often has an unfavorable course and goes away in 60% of patients within two to three weeks.[3] Most people who appear with acute Low Back Pain (LBP) recover rapidly. Still, recurrence instances are thought to be prevalent and are probably largely to blame for the financial burden that LBP causes.[4] LBP is prevalent in high- and middle-income nations and is the main contributor to years of impairment. Furthermore, low-income nations have also shown comparable growth.[5] About sixty billion years of disability were attributed to LBP in 2015, an increase of 54% from 1990.[6] A new meta-analysis on acupuncture to treat chronic pain found that the genuine thing is generally more beneficial than a placebo for cLBP. Additionally, research has indicated that non-specific elements like environment (expectancy) may influence the use of acupuncture and might greatly alter its therapeutic impact.[7] Due to an aging and growing global population, LBP is the primary cause of impairment and carries a growing burden.[8]

Several clinical scales can be used for measuring pain. However, it is unclear what their primary criteria should be for treating LBP patients.[9] Global guidelines advise medical professionals to offer guidance, education, assurance, and basic analgesics, as needed, to manage straightforward, sudden low back discomfort (pain lasting less than six weeks).[10] Costly and highly disabling, low back discomfort is. Understanding the traits of a person with low back pain associated with how well they will heal (often called their ”prognosis”) is crucial. A person's qualities, especially one like years of age, are frequently immutable. Nevertheless, evidence suggests that a person's expectations for recovery could be adjustable. Helping a person have optimistic hopes for their rehabilitation may aid in their recovery if high hopes are linked to better results for back pain sufferers.[11–13] Low back pain is a frequent and incapacitating condition. For this reason, it's crucial for patients, doctors, and those in charge of setting healthcare policy that low back pain be properly treated.[14] Low back pain is frequently treated using Lumbar Manipulative Treatment (SMT), which has been studied in several randomized controlled studies of various quality of methodology and size, with varying outcomes.[15]

In medicine and disease prediction, neutrosophic sets have found a special and useful use, providing a sophisticated way of dealing with the inherent ambiguity and uncertainty in medical data processing. Neutrosophic sets serve a key role in medical research and diagnostic applications, notably in diagnosing and categorizing disorders. Numerous medical disorders include complicated and varied symptoms, making it difficult to properly classify people into certain disease categories. By allowing for an illustration of the degree of truth, indeterminacy, and falsehood in medical data, neutrosophic sets bring a unique method and acknowledge the inherent ambiguity in diagnosis.[16] This has practical ramifications in fields like dorsalgia categorization. Neutrosophic sets allow medical personnel to assess patient data accurately and reach conclusions, especially when typical binary classifications are inadequate. Neutrosophic sets are also increasingly used in customized medicine and the analysis of individual illness risks. With the introduction of genetic and lifestyle data, the ability to accurately predict an individual's susceptibility to developing a certain illness has become a crucial component of preventive healthcare. The probabilistic character of these predictions can be explained by neutrosophic sets.[17] For example, the Neutrosophic method can consider the many levels of evidence, uncertainty, and conflicting aspects within a person's medical history, inheritance, and lifestyle. Neutrosophic sets aid in the creation of more precise and individualized healthcare solutions by recognizing and measuring the uncertainty included in such forecasts. The expanding use of neutrophic sets in medicine emphasizes their importance in improving the precision and effectiveness of illness prediction and individualized treatment therapies.[18]

The CNN-LSTM network design combines LSTM's ability to forecast sequential information with CNN's resilience in feature extraction. The findings show that the CNN-LSTM model performs much better under the DC paradigm.[19] An auto-encoder-based CNN for motor induction diagnostics was also suggested. To anticipate how long turbofan engines will last, LSTM was employed in conjunction with a gated CNN.[20] A technique based on matching templates and CNN was presented to detect hyperbola regions.[21] Dorsalgia, or back pain, may be predicted by considering several variables, including an individual's age, lifestyle, posture, and any underlying medical disorders. Machine learning algorithms can analyze this data to aid in early intervention and preventative measures to forecast the chance of developing dorsalgia. Accurate forecasts could still need continuing observation and clinical assessment to provide individualized therapy. The following are the work's key contributions:

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- The study begins by acknowledging the complexity of dorsalgia prediction and recognizing the importance of demographic, lifestyle, and medical data analysis. This comprehensive approach ensures that all relevant factors are considered in the prediction process.
- Machine learning algorithms and advanced data analytics leverage the collected data effectively. These techniques play a central role in assessing the risk of dorsalgia development, providing a data-driven foundation for prediction.
- A significant contribution lies in adopting EGSFS to identify the most informative features from the original dataset. This step ensures that only the prediction model's most relevant variables are utilized, enhancing its accuracy and interpretability.
- The framework is uniquely trained and fine-tuned using spinal geometry parameters, crucial in dorsalgia prediction. This specialized approach enables precise identification of at-risk individuals, as spinal geometry is directly linked to back pain.
- A novel approach is introduced as a GA-optimized hybrid model, combining CNN and LSTM networks. The GA optimization process fine-tunes the model's architecture and hyperparameters, a crucial step in enhancing its performance, and Single Neutrosophic sets aid in capturing ambiguity, which is particularly beneficial when handling dorsalgia disorders that may present with confusing symptoms, thus enhancing the accuracy of classifying various dorsalgia conditions.
- Finally, the study's findings underscore the potential of this innovative approach to advance preventative and personalized healthcare strategies for back pain management. Early prediction and intervention can significantly alleviate the burden of dorsalgia on individuals and healthcare systems.

The information in this document: The previous work on lung sickness prediction issues utilizing different optimization approaches is examined in Section 2. The issue statement is described in part 3, and the preprocessing, feature selection, and ensemble methods are briefly detailed within subsection 4. The results and discussion are in part 5, and the conclusion is in section 6.

2 Related Work

Öndes et al.[2] proposed Throughout March 2019 and February 2020, a single-center, prospective in nature, randomized clinical trial including 43 individuals; 22 females and 21 males) was carried out. MPT (Multimodal Physical Therapy; 21 individuals) and MPT with TSA (MPT+TSA; 22 individuals) constituted the 2 groups into which those who participated were randomly assigned. The MPT group had 15 sessions of neck-posture exercises, electrical nerve stimulation through the skin, therapeutic ultrasound imaging, and hot packs. Throughout four weeks of therapy, the MPT + TSA group got the identical MPT methodology by adding TSA once per week. Every Neck Disability Index (NDI), Quebec back pain questionnaire (Quebec), Visual Analogue Scale (VAS) for pain, and Spinal Mouse® posture analysis for thoracic kyphosis and thoracic mobility were evaluated at baseline and the fourth week.

Tekin et al.[22] proposed in this research, the frequency of Elastofibroma Dorsi (EFD) in patients with dorsalgia will be assessed using Computed Tomography (CT) imaging of the thorax. Researchers selected and entered information about demographics in a database about patients who were at least 50 years old, had a thoracic CT performed, and had a dorsalgia as their primary complaint when they visited our facility. The group acting as a control was selected from a series of trauma patients who reported to a hospital. They were all in the same age range. Nine patients (9/83, 10.8%) with the common complaint of dorsalgia had no lesions, while 74 patients (74/83, 89.2%) had EFD.

Afonso et al.[23] proposed Due to the dorsal column's close connection to essential organs and its distinct structure, innervation, and rib joint, differential diagnosis of dorsal thoracic discomfort can be difficult. To rule out serious illnesses, the patterns of transferred visceral pain typically necessitate thorough additional diagnostic procedures. Referred discomfort patterns frequently lead to repeated and costly visceral workups to rule out severe illnesses, and degeneration of the costovertebral joint is typically only considered when the cause of the pain is still unclear. The researchers tell the tale of a 40-year-old man who suffered from impairing

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dorsal discomfort due to isolated costovertebral bone loss. After a medication was injected under computed CT guidance, the symptoms were under control. This case study attempts to explain the clinical appearance of an uncommon entity that must be considered when making a back pain alternative diagnosis.

Blass et al.[24] proposed Endometrial materials frequently transplanted in the pelvic peritoneum in extrauterine regions due to menstruation. Estimates of the overall incidence of endometriosis range from 5 to 10% of all women of reproductive age. Researchers included more than 1000 variables from UKBB containing details on women's health and way of life, as well as genetic variations and medical history before endometriosis was diagnosed. They trained a model to detect endometriosis using machine learning techniques. With a 0.78 area under the ROC curve (roc-AUC), the gradient boosting methods of CatBoost were able to provide the best predictions for the data-combined model.

The binary categorization method utilizing ensemble neural networks and interval neutrosophic sets was proposed by Kraipeerapun et al.[25] The subject of binary categorization is addressed in the study using an ensemble neural network and interval neutrosophic sets technique. An ensemble of pairs of neural networks built to forecast values for degree of truth membership, indeterminacy membership, and false membership in the interval neutrosophic sets are subjected to a bagging procedure. The study also includes the classification process and quantifying error and ambiguity. Many aggregating methods are suggested in this study. Researchers applied the methods to the well-known benchmark issues from the UCI machine learning library, such as the ionosphere, diabetes in Pima Indians, back discomfort, and liver illnesses. The methods outperform the current methods, which exclusively apply to the true membership values regarding categorization effectiveness. Additionally, the outcomes of the suggested ensemble strategies are superior to those produced by a single pair of neural networks.

Li et al.[26] Proposed chronic Back Pain (CBP) is a regressive medical condition that affects the patient's behavior and brain health. There is growing evidence that CBP may modify how neurons in the brain are organized. Nevertheless, it is unclear whether or not the severity of CBP is related to changes in the dynamics of functional network structure. Using a window-sliding approach, we created dynamic functional networks based on rs-fMRI data from Within the Open Source Pain database: 34 patients with CBP and 34 matched by age Healthy Controls (HC). Following that, we collected the attributes of each window's nodal degree, Clustering Coefficient (CC), and Involvement Coefficient (PC) to describe developments in network topology over time. To measure the longitudinal divergence of each network characteristic that distinguishes a patient with CBP from the typical oscillation of the HCs, a unique feature called the Temporal Grading Index (TGI) was developed.

3 Problem Statement

Based on the knowledge gained from the related studies, it is clear that chronic back pain (CBP) is a complicated health issue that affects a person's behavior and cognitive and physical health. The results of the current investigations have suggested that CBP may cause changes in how brain networks are organized, underscoring the need to have a thorough knowledge of these changes. However, the issue still stands that there is a critical knowledge gap regarding the complex relationship between the severity of CBP and alterations in the brain's functional network architecture. To address the broader effects of CBP on the patient's general health and design interventions and therapies that are successful, this information gap provides a substantial obstacle.[26] Our proposed study uses resting-state rs-fMRI data gathered from CBP patients and age-matched unaffected controls to get around this problem. The study intends to quantify changes in key network features, such as nodal degree, clustering coefficient, and participation coefficient, over multiple time scales by using a sliding window technique. The Temporal Grading Index, a brand-new measure that we offer, allows us to objectively evaluate how much each network feature of a CBP patient differs from the normal oscillations seen in healthy control patients. Our research aims to clarify the unpredictable shifts in brain network architecture that relate to the severity of CBP using this novel methodology. By filling up this important information vacuum, we want to understand the neurological components of CBP further and, ultimately, encourage the creation of more efficient methods for the condition's diagnosis, management, and therapy.

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4 Proposed Genetic Algorithm-Optimized Hybrid CNN-LSTM Framework

The dataset used in this work has 13 characteristics, 12 numerical predictors, and 1 binary class attribute, allowing for a thorough categorization of dorsalgia situations. The preparation stage includes anomaly elimination, filling in missing or zero values and data normalization to ensure data quality. The most useful qualities are then chosen for study using an EGSFS approach. The next step is introducing a hybrid model for dorsalgia categorization that combines a CNN and an LSTM architecture, with the CNN component extracting spatial information from spinal data and the LSTM network capturing temporal relationships. The model is further optimized via genetic algorithms. Neutrosophic sets are included in the categorization procedure to overcome dorsalgia categorization's inherent ambiguity and complexity, enabling more precise and context-aware diagnosis. Neutrosophic sets evaluate each instance's truth, indeterminacy, and falsity-membership, offering a sophisticated framework for dealing with ambiguous and uncertain conditions. This comprehensive strategy aims to improve the robustness and accuracy of dorsalgia categorization, ultimately resulting in more individualized and successful healthcare approaches for people with back pain issues. Figure 1 shows the Overall Architecture of the Proposed Framework.

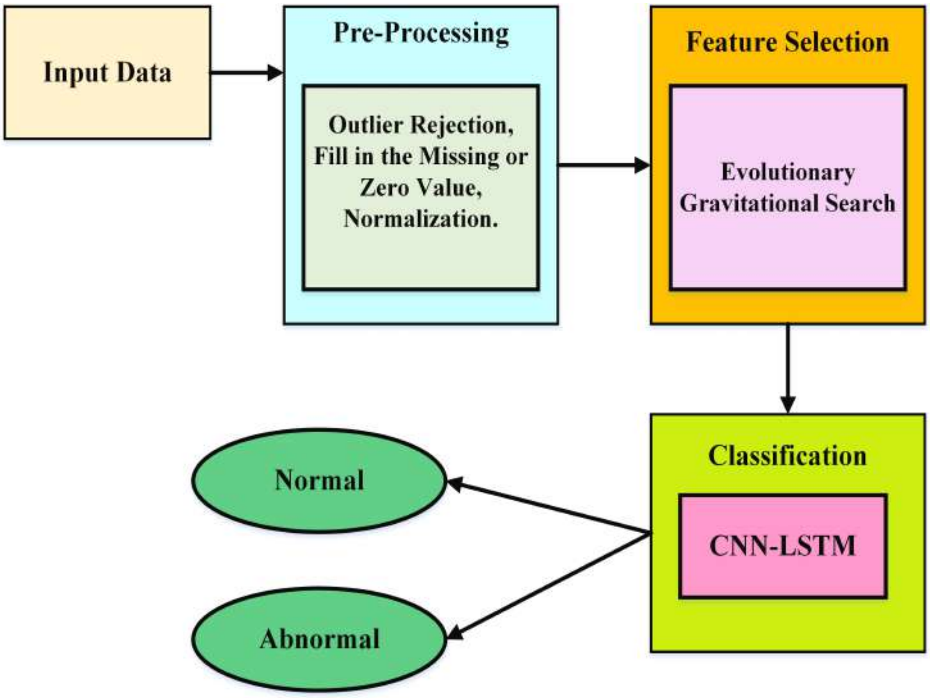

Figure 1: Overall Architecture of the Proposed Framework.

4.1 Data collection

13 Attributes, 12 Numeric Predictors, and 1 Binary Class Attribute (No Demographics), 310 Observations Numerous issues by any section of an intricate, interrelated system of spinal ligatures, discs, muscle tissue, and bones in the lumbar vertebrae can result in lower back discomfort. The following are typical causes of lower back pain: The large nerve roots in the lower back that go to the legs may be irritated:

- Irritation of the smaller neurons supplying the lower back is possible.
- A strain might occur in the big, paired lumbar muscles (erector spine).
- Musculoskeletal joints, ligaments, or bones might be hurt.
- A disc in the spine might be deteriorating.

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Back muscle spasms, which may not seem like much but can cause excruciating pain and incapacity, are a common side effect of lower back disorders. Although lower back pain is quite prevalent, there is a wide range of signs, symptoms, and intensity. Simple lower back muscle strains may be so painful as to need a trip to the ER, but a degenerating disc may only produce minor, sporadic discomfort. Using information about the physical spine that has been gathered, this collection of facts will determine if a person is abnormal or normal. Here, 20% is training data, and 80% is testing data.[27]

4.2 Pre-Processing

4.2.1 Pre-Processing

The outlier's observation is notably different from other viewpoints. Data must be eliminated from data distribution because classifiers are sensitive to ranges and attribute distributions. The mathematical formulation in this study for outlier rejection may be phrased as follows, as illustrated in equation (1):

$$L(x) = \begin{cases} x, & I_1 - 1.5 \times IQR \leq x \leq +1.5 \times IQR \\ reject, & otherwise \end{cases} \tag{1}$$

Those are in n- the dimensions of which x indicate the occurrences of the feature vector, $x \in J^n$. I_1,I_3, and IQR the first, third, and interquartile ranges, respectively, where I_1,I_3,$IQR \in J^n$.

4.2.2 Fill in the Missing or Zero Values

After discarding the outlier attribute values, the method used for filling in the gaps or negative data has to be carried out since they may give a classification algorithm an erroneous forecast. The recommended design assumes that the characteristic's values are mean with missing or null values extended as in Equation (2), as opposed to exclusions. The mean gains from imputation when the continuous data is imputed without adding outliers.

$$I(x) = \begin{cases} mean(x), \; if\, x = null/missed \\ x, \;\; otherwise \end{cases} \tag{2}$$

The indicator vector x includes occurrences in n dimensional space, $x \in J^n$.

4.2.3 Normalization

highest value for each feature has a unique distribution. Artificial neural networks struggle to match the data in certain circumstances. It tries to modify each characteristic so that the range of the real numbers set is comparable. There are so many various ways to approach this issue. For all symbols to communicate property values in the lower back pain symptoms dataset, numerical property values are encoded using on-hot encoding. After the data has been transmitted, each symbolic attribute is given a numeric value. Data scaling ("data normalization") normalizes various data attributes. Use of maximum-minimum normalization to scale feature values. Equation (1)'s range of [1, 2] is normalized within all feature values.

$$\hat{d} = \frac{d - d_{\min}}{d_{\max} - d_{\min}} \tag{3}$$

Here d the sample value is indicated, $d_{\min}$ shows the base value, and $d_{\max}$ indicates the highest value for each characteristic.

To get the mean and standard deviation of the data, utilize Equation (2)'s description of the standard typical distribution.

$$\hat{d} = \frac{d - \mu}{\sigma} \tag{4}$$

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Here is the meaning of μ:

$$\mu = \frac{1}{M}\sum_{i=1}^{M} d_q \tag{5}$$

Their standard deviation of σ is:

$$\sigma = \sqrt{\frac{1}{M}\sum_{i=1}^{M}(d_i - \mu)^2} \tag{6}$$

Here Mindicate the sample's number and $d_i$denotes the dataset $i^{th}$of element.

Logarithm standardization is used to apply a logarithmic scale to the data in equation (5) below.

$$\hat{d} = \log(d) \tag{7}$$

4.3 Evolutionary Gravitational Search-Based Feature Selection (EGSFS)

EGSFS has been demonstrated to be an effective meta-heuristic by employing Newton's equations of gravitation and motion. Particles can attract one another due to gravitational forces. This force pushes the lighter thing in the direction of the heavier object. The movement of heavy things will be slower, which is seen to be a preferable option. This behavior in EGSFS ensures the exploitation phase. $M$is grouping of searchers (in numbers) in the field of search area $m$dimensions, and the vector represents where they were located in the search area D_i:

$$D_i = (d_i^1, ..., d_i^x, ..., d_i^m),\ i = 1, 2, ..., M \tag{8}$$

$$N_i(t) = \frac{fit_i(t) - worst(t)}{\sum_{j=1}^{M}(fit_j(t) - worst(t))} \tag{9}$$

Here $N_i$and $fit_i(t)$indicates mass value fitness go-between $i-th$and time t, $worst(t)$is all managers at time t(current population) worst agent. Agents move iteration points about to find uncharted territory in feature space. EGS-FS reports that a new post of an agent is computed by averaging its most recent velocity and location$v_i(t+1)$, as in the equation:

$$D_i(t+1) = D_i(t) + v_i(t+1) \tag{10}$$

An object's subsequent velocity is calculated by dividing its current mobility by acceleration:

$$v_i(t+1) = g \times v_i(t) + y(t) \tag{11}$$

Here g indicates an adjustable at random between 0 and 1. Calculating the particle's acceleration i may be achieved by dividing the particle's mass by the gravitational pull of other particles. i, according to the equation.

$$y_i(t) = \frac{\sum_{j=1, j\neq i}^{M}(k \times T_{ij}(t))}{N_i(t)} \tag{12}$$

Here k represents an accidental mutable between (0,1), $T_{ij}(t)$ evidence of force operating on particles $j$on the subdivision $i$in the repetition. Newton's gravitational law may be used to determine force.

$$T_{ij}(t) = Gra(t)\frac{N_i(t) \times N_j(t)}{G^2}(D_j(t) - D_i(t)) \tag{13}$$

Here Gra demonstrates, that the force of gravity G indicates the distance separating particle i and particle$j$. In EGS-F, Grawill be decreasing function, and the starting value $Gra(Gra_0, t)$is to search process control.

In addition to filter techniques, researchers have also employed evolutionary algorithms to discover optimum feature subsets in the past. The total number of features chosen by the filter technique is the dimension of the information gain-based feature ranking, with 1 denoting the existence of a feature and 0 denoting its absence in our method. During the fitness function's evaluation of each attribute based on the data gathered the particle's velocity and location are adjusted for each iteration using the formula below:

$$f_{ij}^{t+1} = c \times f_{ij}^{t} + w_1 \times rand \times (lbest - d_{ij}^{t}) + w_2 \times rand \times (sbest - d_{ij}^{t}) \tag{14}$$

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$$d_{ij} = \begin{cases} 1, & if\, rand < G(f_{ij}) \\ 0, & otherwise \end{cases} \tag{15}$$

Here

$$G(f_{ij}) = \frac{1}{1 + e^{-f_{ij}}} \tag{16}$$

$$d_{ij}^{t+1} = d_{ij}^{t} + f_{ij}^{t+1} \tag{17}$$

Here $f_{ij}^{t+1}$is speed at $(t+1)$repetition and d_{ij}^{t+1} indicates an element's location at$(t+1)$ restatement, c signifies the inertia of weight $lbest$ indicates the finest place, $sbest$ shows the greatest position worldwide,$rand$specifies random value, $w1$indicates parameter cognitive, $w2$denotes social parameter among 0 and 1. Obtain the best characteristic subset list $k1$ and eliminate the unnecessary component built with m samples and$k1$ a new review vectoring feature using features. After filtering, only relevant characteristics are obtained.

4.4 Classification using CNN-LSTM

In the context of dorsalgia classification, a Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM) hybrid model can be employed to diagnose and classify different types of back pain effectively. The extracted features are then fed into an LSTM network, which excels at modeling sequential dependencies and capturing temporal information. This is crucial in assessing the progression or changes in dorsalgia conditions over time. By integrating both spatial and temporal aspects, the CNN-LSTM model can offer improved accuracy in identifying and classifying dorsalgia conditions, aiding in more precise diagnoses and treatment decisions for patients with back pain.

4.4.1 Convolutional Layer

The convolutional layer, which has the strongest signature, is the first stage of a CNN classification process. The local operation aims to effectively categorize the input images by extracting various patterns from them. Let $X^n \in R^{M^n \times N^n \times D^n}$ be our N-th convolutional layer's input and $F \in R^{m \times n \times d^n \times s}$be an order four vector expressing the location width s kernels of the N-th layer. The result of the N-th convolutional layer will be an order three vector with the notation$Y^k \in R^{M^n - m+1 \times N^n - n+1 \times s}$, with the components resulting from,

$$Y_{i^n, j^n, s} = \sum_{i=0}^{m} \sum_{j=0}^{n} \sum_{l=0}^{d^n} F_{i,j,d^n} \times X_{i^n, j^n, l}^{n} \tag{18}$$

If a geographic location satisfies the conditions $0 = i^n = m^n - m + 1$ and $0 = j^n = N^n - n + 1$, the Equation (10) must be performed for all $0 \leq s \leq S$. Typically, Convolutional neural networks (CNNs) use a lot of convolutional layers to identify more apparent spatial patterns in the input images. Convolutional layers guarantee that the image's dimensions remain consistent throughout the procedure with zero padding.

4.4.2 Pooling Layer

Let the N-th layer, now a spatial range of$m \times n$, have as its input $X^n \in R^{M^n \times N^n \times D^n}$.Because there are no variables for these layers to be learned, they are parameter-free. The result is a tensor of order three indicated by$Y^n \in R^{M^{k+1} \times N^{n+1} \times D^{n+1}}$, where

$$M^{n+1} = \frac{M^n}{m}, N^{n+1} = \frac{N^n}{n}, D^{n+1} = D^n \tag{19}$$

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Whereas the pooling layer handles the X^n channel individually, one at a time. While many distinct pooling techniques exist, average and maximum pooling are increasingly popular. Our study used max pooling, and the outcomes were predicated on a formula.

$$y_{i^n,j^n,d} = \max_{0 \leq i \leq m, 0 \leq j \leq n} x^n_{i^n \times m+i, j^n \times n+j,d} \tag{20}$$

Where $0 = i^n = M^n, 0 = j^n = N^nand0 = d = D^n$. It is reasonable to use pooling layers to minimize output tensor size while maintaining the most crucial properties found.

4.4.3 Fully Connected Layer

A categorization operation, such as softmax, sigmoid, tanh, etc., always follows the last fully connected layer. The real value Y_j it produces is compared to the anticipated valueY_j using the chosen loss function. In this situation, we believe that using the sigmoid function.

$$y_j = \frac{e^{x_j}}{1 + e^{x_j}}, x_j \in R \tag{21}$$

This would be suitable for this binary issue. The likelihood that the input picture shows the presence of an intuitively represented by the expression $y_j \in (0, 1)$.

It returns the parameters pertaining to a particular number of network nodes to zero. Last but not least, the procedures of batch normalization and ReLU function as vital transitional mechanisms connecting the levels discussed before. The ReLU function is defined as

$$y_{i,j,d} = max\left(0, x^n_{i,j,d}\right) \tag{22}$$

Batch normalization speeds up and improves the stability of neural networks by normalizing the layer's input by rescaling and re-entering after each iteration. It accomplishes this by attempting to transmit just the elements that are necessary for the categorization with $0 = i = M^n, 0 = j = N^n$ and $0 = d = D^n$.[28]

4.4.4 LSTM

The LSTM autoencoder model's choice of the best during training varies from imprecise to accurate. The LSTM encoder gathers real-time and historical data on resource usage, which is normalized to produce and feed $l$input values such as $\{x_1, x_2, ...x_l\}$into the input layer.

$$v_h = \sigma(C_{vt}t_{h-1} + C_{vd}d_h + z_v) \tag{23}$$

$$q_h = \sigma(C_{qt}t_{h-1} + C_{qd}d_h + z_q) \tag{24}$$

$$\tilde{w}_h = \tan t(C_{\tilde{w}t}t_{h-1} + C_{\tilde{w}d}d_h + z_{\tilde{w}}) \tag{25}$$

$$w_h = v_h.w_{h-1} + q_h.\tilde{w}_h \tag{26}$$

$$k_h = \sigma(C_{kt}t_{h-1} + C_{kd}d_h + z_k \tag{27}$$

$$t_h = k_h. \tan t(w_h) \tag{28}$$

In contrast to feed forward neural networks, LSTM can handle variable length inputs and outputs and process any length sequence. It is capable of digesting contextual information and having a high long-term memory. Additionally, LSTM can resolve RNN's problems with growing and receding gradients. It also offers improved processing capability for forecasting volatile time series and can quickly adapt to sudden changes in the tread.

$$W_t = \sum_r^H \alpha_{qr}t_r \tag{29}$$

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The weight $\alpha_{qr}$of each hidden state $t_r$is calculated by

$$\alpha_{qr} = \frac{\exp(u_{qr})}{\sum_o^h \exp(u_{ik})} \tag{30}$$

Where $u_{qr} = y(G_{q-1}, t_r)$

An initial input starts the decoder's input sequence, and the subsequent inputs make up the decoder's output at the final time step.

4.4.5 Generic Algorithms

It is crucial to remember that evolutionary algorithms swiftly locate solutions in the solution space without being entangled in locally optimum solutions. The genetic algorithms' primary calculating flow is as follows:

Generic algorithms employ a predetermined quantity of binary code in a predetermined set of parameters. Several types of coding may be used depending on the issue; for instance, a genuine type of code can be used to handle the issue of the traveling salesman.

Identification and assessment of fitness value: The benefits and drawbacks of a genetic generation's members can be identified using various evaluation criteria, and adaptation and environment will continue to be iterative factors.

Select: By locating people who are well acclimated to their surroundings, new groups may be formed. There are several ways to pick the approaches, which may be applied based on the difficulty.

Cross: Choosing randomly acquired offspring that replace one or more with a specified probability might boost the capability of the global search algorithm.

The variation entails picking one or more points in the produced binary data and altering them, for example, from a "0" to a "1". Figure 2 shows pseudocode for a genetic algorithm.

G==1
Initialize P_G
Evaluate P_G
While G≤ N_G
Mutate P_G and generate CM_G
Crossover P_G and generate CC_G
$C_G == cm_G \chi cc_G$
$E_G == P_G \chi C_T$
Select P_{G+1} *from* E_G
Increment G
End while

Figure 2: Pseudocode for a Genetic Algorithm.

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4.4.6 Neutrosophic Classification

Neutrosophic sets provide an innovative and important method for addressing the widespread ambiguity and confusion surrounding distinguishing different kinds of back pain disorders in dorsalgia categorization. In the categorization procedure, the Single Neutrosophic sets aid in capturing ambiguity, which is particularly beneficial when handling dorsalgia disorders that may present with confusing symptoms. Dorsalgia can be difficult to classify using traditional methods because of its complex and sometimes unidentified symptoms. By recognizing that each example may concurrently exhibit varying degrees of truth, indeterminacy, and falsehood, Neutrosophic sets lead to a perspective transformation. Neutrosophic sets effectively represent the inherent ambiguity in medical diagnostics, providing them with a highly adaptive structure for exploring complex dorsalgia surfaces. The categorization model can function within the variation and complexity of real-world medical circumstances because neutrophilic sets measure the membership level to several classes and the indeterminacy associated with each instance. They provide more precise and individualized treatment strategies for people with dorsalgia disorders because they enable more complex and context-aware diagnoses.

Neutrosophic Set Representation

The categorization of each illustration can be represented by a Single Neutrosophic set. The truth-membership (T), indeterminacy-membership (I), and falsity-membership (F) functions combine the components of the Neutrosophic set.

Truth-Membership Function (T(x)): The extent to which a particular example complies with a given class is indicated by this component.

$$T(x) \ = \ P \left(Class \; x \; is \; True \right) \tag{31}$$

The degree to which a certain example corresponds to the class of Dorsalgia is quantified by Equation (31).

Indeterminacy-Membership Function (I(x)): The level of uncertainty or ambiguity in the categorization is represented by this component.

$$I(x) \ = \ P \left(Class \; x \; is \; Indeterminate \right) \tag{32}$$

Equation (32) measures the degree of ambiguity or uncertainty related to the Dorsalgia categorization.

Falsity-Membership Function (F(x)): This element reflects the extent to which a specific instance deviates from a certain class.

$$F(x) \ = \ P \left(Class \; x \; is \; False \right) \tag{33}$$

Equation (33) measures the extent to which a certain case deviates from the Dorsalgia class. These three memberships should add up to 1, suggesting that an instance may be true, indeterminate, or false. Neutrosophic sets can be used to account for the ambiguity in the categorization of dorsalgia conditions. This method offers a more sophisticated and adaptable strategy to manage situations where symptoms do not unambiguously point to a certain form of back pain. Additionally, it makes unresolved or borderline circumstances easier to represent.

5 Results and Discussion

Present the outcomes of applying a Genetic Algorithm-Optimized Hybrid CNN-LSTM Framework to predict dorsalgia based on spinal geometry parameters. Our findings reveal that the hybrid model exhibits exceptional performance in accurately predicting dorsalgia, outperforming traditional machine learning techniques and single-model approaches. Through the fusion of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, the model effectively captures both spatial and temporal dependencies in the spinal geometry data, enhancing its ability to identify subtle patterns and variations associated with dorsalgia. Moreover, the genetic algorithm optimization further fine-tunes the model's hyperparameters, leading to improved predictive accuracy. By including neutrosophic sets into the classification process, which enables more

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accurate and context-aware evaluation, dorsalgia intrinsic ambiguity and complexity are addressed. Neutrosophic sets provide a comprehensive framework for handling ambiguous and uncertain situations by evaluating each instance's truth, indeterminacy, and falsity-membership. This study demonstrates the promising potential of advanced deep learning techniques and optimization strategies in the field of medical diagnostics, particularly for disorders related to spinal health like dorsalgia, offering new insights and opportunities for early detection and intervention.

5.1 Accuracy

How frequently the classifier makes the right assumption is shown by its accuracy. The ratio of accurate forecasts to all other credible hypotheses is known as accuracy. Eqn (34) is a demonstration of it.

$$Accuracy = \frac{T_{pos} + T_{neg}}{T_{pos} + T_{neg} + F_{pos} + F_{neg}} \tag{34}$$

5.2 Precision

The amount of correctly classified outcomes is determined by calculating the precision, or level of accuracy, of a classifier. Fewer false positives result from increased accuracy, while many more do so from decreased precision. The percentage of instances that are correctly categorised to all occurrences is the definition of precision. Eqn (35), which defines it.

$$P = \frac{T_{pos}}{T_{pos} + F_{pos}} \tag{35}$$

5.3 Recall

The sensitivity of a categorization, or how much relevant data it produces, are determined by recall. The overall amount of FN reduces with improved recall. Recall is the ratio of cases that have been correctly categorised to all of the predicted occurrences. Eqn (36) provides evidence for this.

$$R = \frac{Tpos}{Tpos + Fneg} \tag{36}$$

5.4 F-Measure

The combined metrics known as F-measure, which reflects the weighted mean of recall and accuracy, are obtained by adding precision and recall. Eqn (37) identifies it as being so.

$$F\ measure = \frac{2 \times precision\ \times recall}{precision \times recall} \tag{37}$$

5.5 False Positive Rate

The percentage of situations when a desirable outcome was expected but not achieved. Eqn (38), the equation, is shown.

$$FPR = \frac{F_P}{T_N + F_P} \tag{38}$$

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5.6 False Positive Rate

The percentage of positive occurrences that were expected to be negative but ended up being positive, as well as the equation, are displayed in Eqn. (39).

$$FNR = \frac{F_N}{T_P + F_N} \tag{39}$$

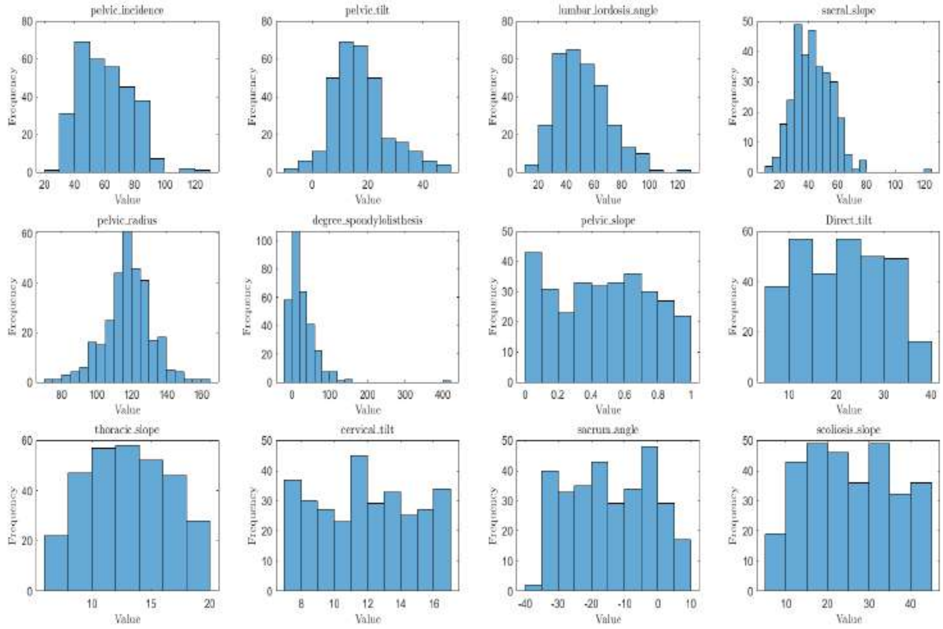

Figure 3: Collection of Physical Spine Data.

Figure 3 shows the analysis of the Lower Back Pain Symptoms Dataset revealed the critical role of various spinal parameters in assessing and understanding lower back pain symptoms. Among these parameters, pelvic incidence, pelvic tilt, lumbar lordosis angle, sacral slope, pelvic radius, degree of spondylolisthesis, pelvic slope, direct tilt, thoracic slope, and cervical tilt were all found to be highly informative indicators. Pelvic incidence, for instance, represents the orientation of the pelvis, and we observed a strong association between higher pelvic incidence values and an increased likelihood of experiencing lower back pain. Similarly, lumbar lordosis angle, which denotes the curvature of the lower spine, showed that deviations from the norm were correlated with varying degrees of discomfort. Additionally, the degree of spondylolisthesis, indicating the extent of vertebral displacement, was a crucial factor in determining the severity of lower back pain. These findings emphasize the significance of considering multiple spinal parameters in assessing lower back pain symptoms, providing a more comprehensive understanding of the condition and its potential causes.

In Figure 4, present a comprehensive overview of the variables contained within our dataset. These variables are crucial components that capture various aspects of the data and are instrumental in our analysis. They include essential attributes such as demographic information, time-related metrics, and outcome measures, providing a well-rounded foundation for research findings. In the subsequent sections, we will delve into the specific roles and significance of these variables in our study, highlighting their contributions to the results and conclusions presented herein.

Figure 5, the Parallel Coordinate Graph, visually represents the intricate relationships and patterns among multiple variables simultaneously. This graph serves as a powerful visualization tool, enabling us to discern trends, correlations, and outliers across our dataset effectively. In our results section, we will interpret the insights gained from this graph to provide valuable context and key findings that contribute to the overall understanding of our study's outcomes.

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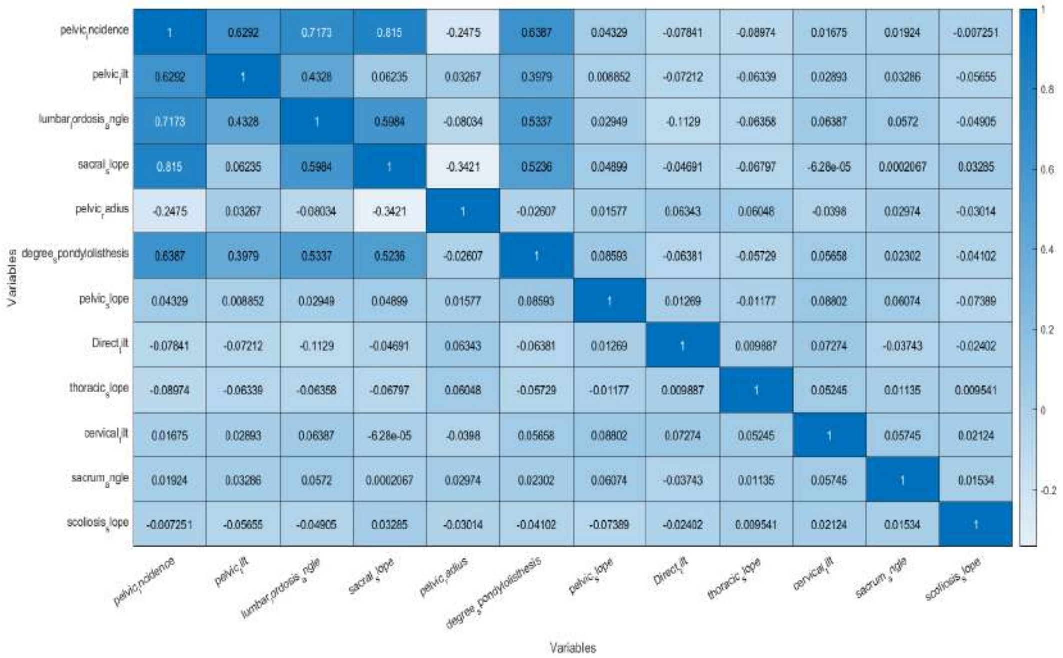

Figure 4: Variables in the Dataset.

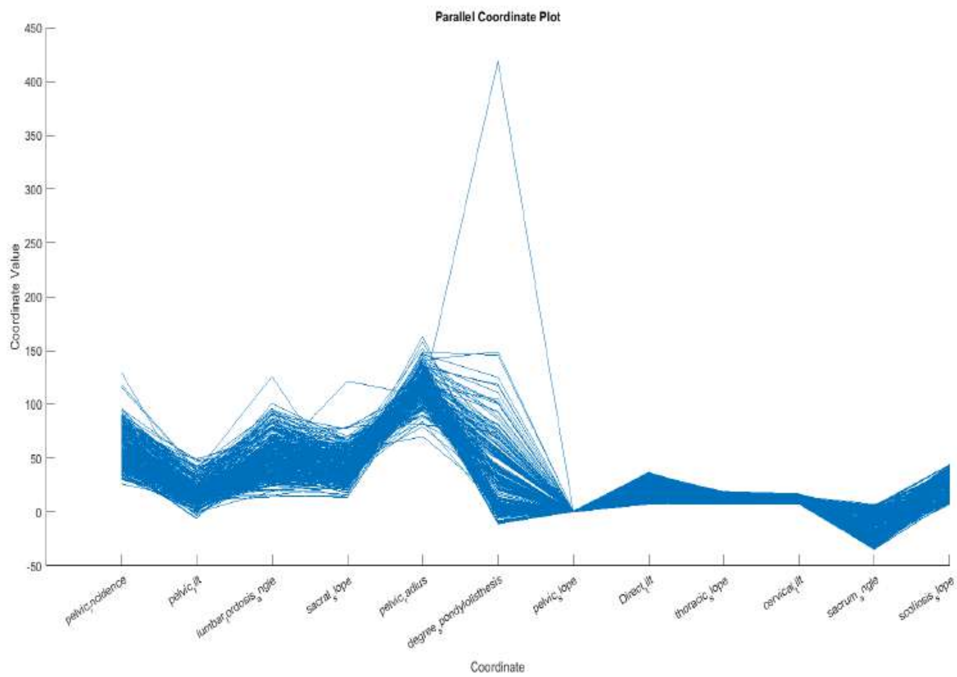

Figure 5: Parallel Coordinate Graph.

In Figure 6, present the training time accuracy and loss plot, which illustrates the performance of our machine learning model over the course of training. This graph offers a dynamic view of how accuracy and loss metrics evolve during the training process, shedding light on the model's learning dynamics. The results section will utilize this figure to analyze the convergence behaviour of the model, identify optimal training epochs, and discuss the implications of its performance on the overall success of our study.

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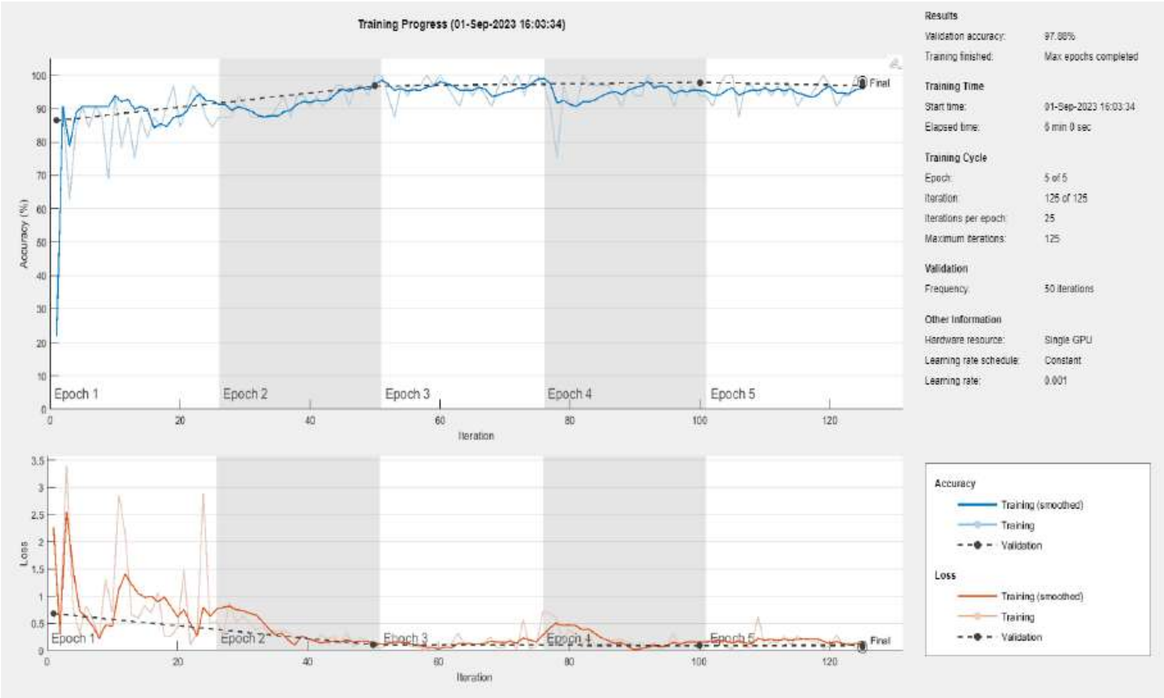

Figure 6: Training Time Accuracy and Loss.

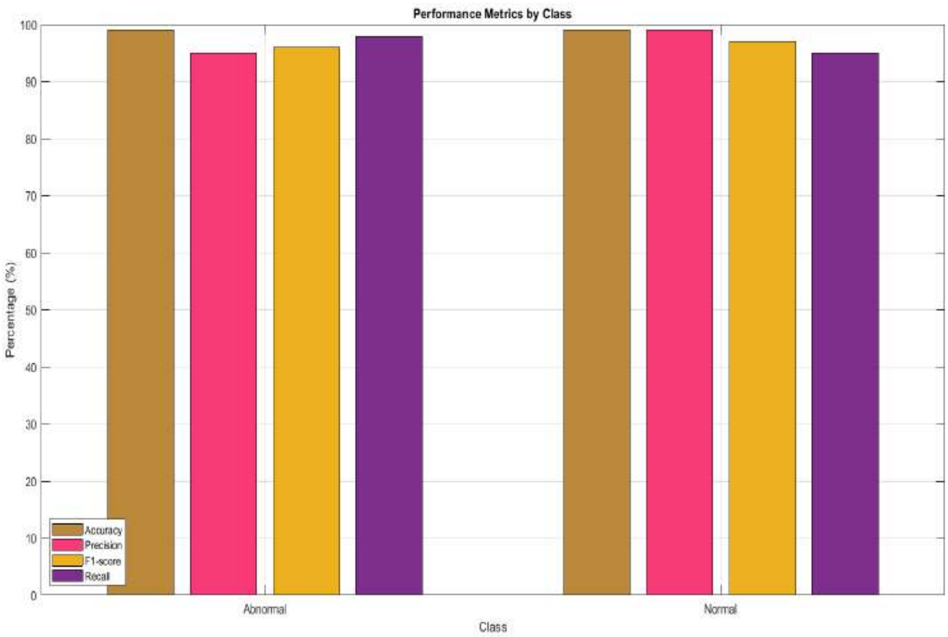

Figure 7: Performance Metrics Graph.

In Figure 7, our Performance Metrics Graph provides a comprehensive overview of key evaluation metrics, including accuracy, precision, recall, and F1-score, for both normal and abnormal classes in our classification task. This graph serves as a critical reference point for assessing the model's performance and its ability to distinguish between the two classes. In the results section, we will leverage this figure to draw meaningful insights into the model's effectiveness, highlighting its strengths and potential areas for improvement in classifying normal and abnormal instances.

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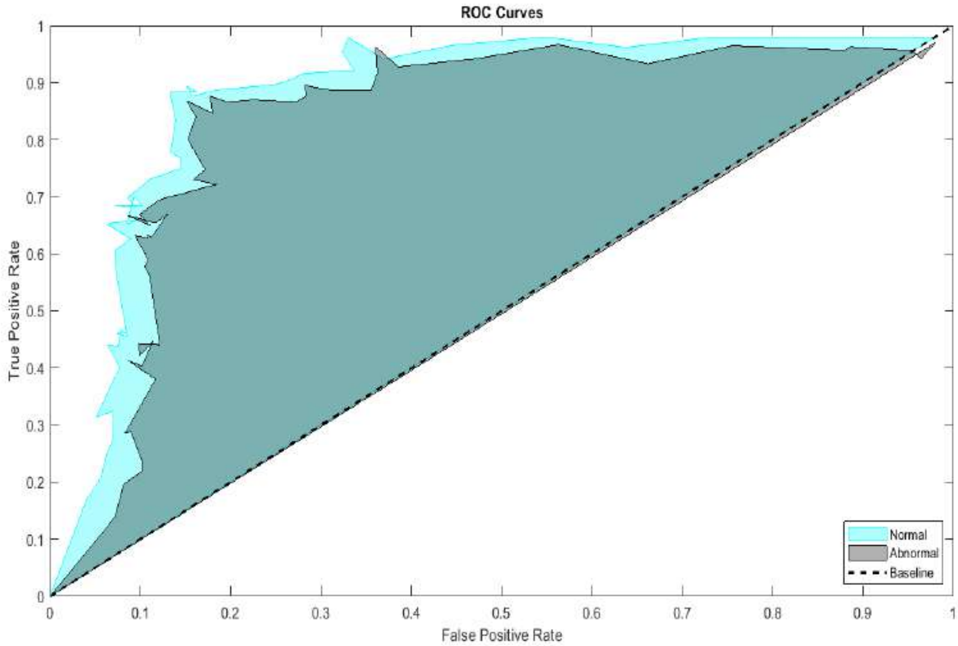

Figure 8: ROC Curves.

In Figure 8, the ROC curves are presented, with the blue curve representing the normal class and the grey curve representing abnormal instances. The clear separation between these curves signifies the model's effectiveness in discriminating between normal and abnormal data.

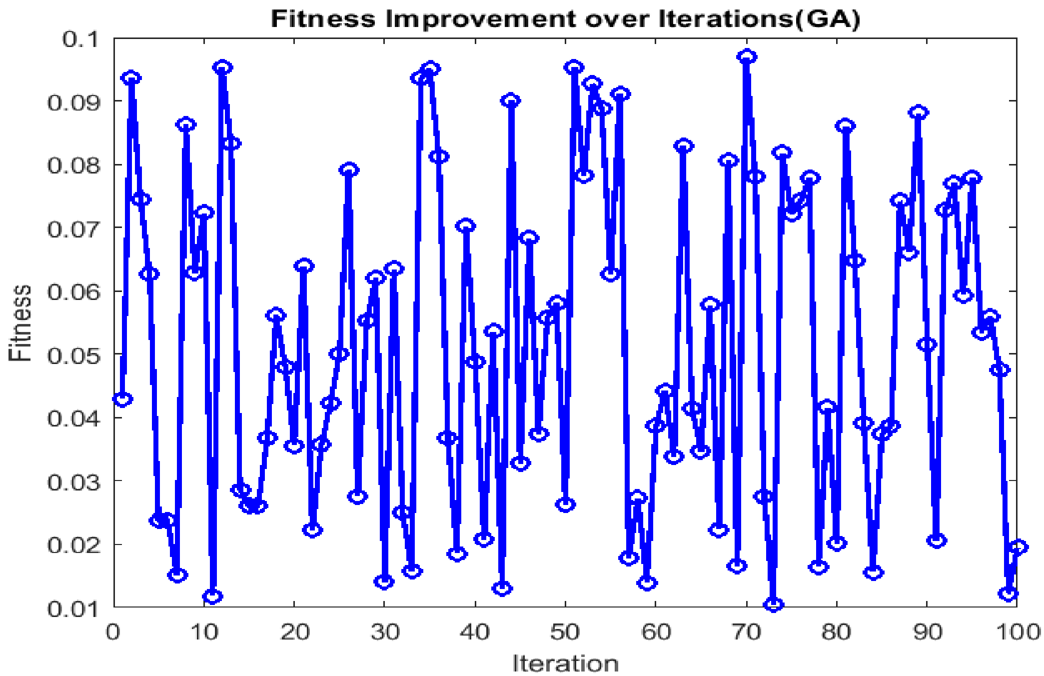

Figure 9: Improve the Fitness Graph.

Figure 9 illustrates the improvement in fitness over successive iterations. The graph demonstrates how the fitness score, a measure of model performance, evolves as the optimization process progresses. Observing

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whether fitness stabilizes or continues to improve can inform decisions about when to halt the optimization process.

Table 1: Comparison of Proposed Algorithms with Other Existing Methods.

Prediction Methodology	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
Logistic Regression	87	86.7	86.7	87.2
Convolutional Neural Network	92	91.3	92.1	91.7
Decision Tree Classifier	79	78	78	78
Random Forest	94	94.3	94.3	94
Support Vector Machine	88	88	89	88
Proposed	99	99.4	99.6	99.4

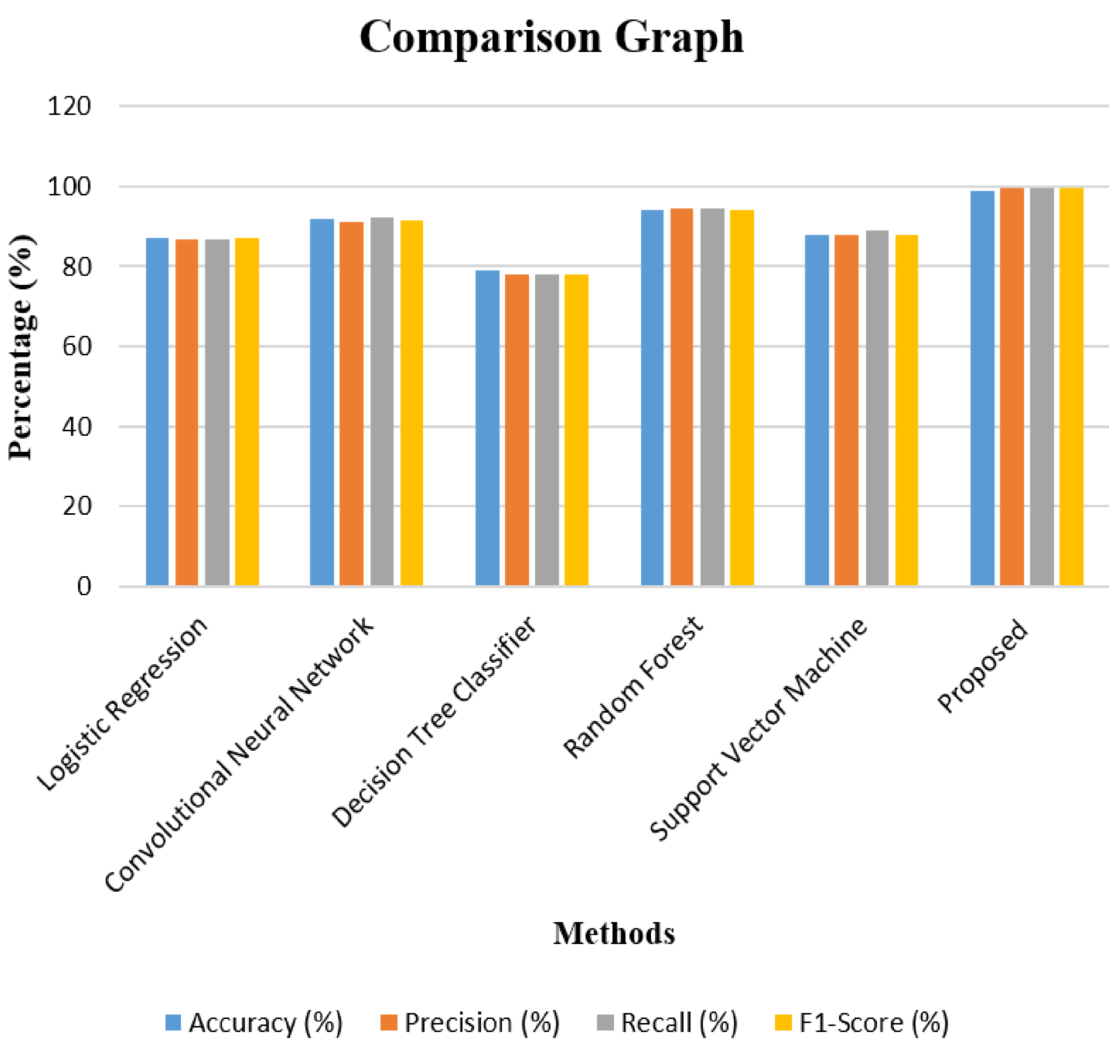

Figure 10: Comparison of Proposed Algorithms with Other Existing Methods.

The suggested approach is compared to many other algorithms for predicting dorsalgia situations based on important performance indicators in Table 1 and Figure 10. Logistic Regression, Convolutional Neural Network, Decision Tree Classifier, Random Forest, and Support Vector Machine are among the techniques that were

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tested. Accuracy, precision, recall, and F1-score are measured parameters. According to the data, the suggested strategy works better than all other approaches, obtaining an amazing accuracy of 99%, high precision (99.4%), recall (99.6%), and F1-score (99.4%). With accuracy rates of 87% and 79%, respectively, alternative approaches like Logistic Regression and Decision Tree Classifier perform more complicated. Although they perform better than the suggested technique, with accuracy levels of 92% and 94%, the Convolutional Neural Network and Random Forest remains low. These results highlight the proposed algorithm's exceptional prediction ability and efficiency in categorizing dorsalgia situations, making it a potential and reliable tool for improving individualized healthcare approaches in the treatment of back pain problems.

6 Conclusion and Future Work

In this research, we have demonstrated the effectiveness of a multifaceted approach for predicting dorsalgia, emphasizing the importance of demographic, lifestyle, and medical data analysis. Leveraging machine learning algorithms and advanced data analytics has allowed us to forecast the risk of developing back pain with a high degree of accuracy. Early prediction not only facilitates proactive interventions but also enables the implementation of personalized healthcare strategies, ultimately alleviating the burden of dorsalgia on both individuals and healthcare systems. A significant contribution of this work lies in the feature selection process, where the EGSFS method was employed to extract the most informative features. By incorporating spinal geometry parameters into our predictive model, we have enabled precise identification of individuals at risk, enhancing the clinical utility of our approach. Moreover, the introduction of a GA optimized hybrid CNN and LSTM model represents a novel advancement in classification tasks. The GA optimization process fine-tuned the model's architecture and hyperparameters, resulting in a substantial improvement in classification accuracy. Dorsalgia's inherent ambiguity and complexity is solved by incorporating neutrosophic sets into the categorization procedure, which permits more precise and context-aware assessment. Neutrosophic sets offer a thorough framework for dealing with ambiguous and uncertain circumstances by assessing the truth, indeterminacy, and falsity-membership of each instance. Our experiments on a lower back pain symptoms dataset revealed an impressive accuracy rate of 99%, highlighting the potential of this hybrid model for real-world applications. The future scope of this work includes exploring the integration of real-time sensor data and wearable technology to enhance the accuracy and timeliness of dorsalgia prediction, further advancing proactive healthcare interventions and personalized treatment strategies. Expanding the dataset to improve model generalization and investigating the integration of multimodal data sources might be the main goals of future study for this article. For practical deployment, it would also be beneficial to incorporate explainable AI approaches to offer information about the decision-making procedure of the model and additional validation through clinical experiments. The investigation of real-time monitoring along with prompt intervention techniques for the management of dorsalgia may be a crucial area for future study.

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