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Severity Classification of Electronic Health Records of Leprosy Patients Using Chicken Swarm Optimization-based LSTM Model

Jalpa Darshit Mehta*[1], Alok Kumar[2], Prasun Chakrabarti[3]

[1]Sir Padampat Singhania University, Udaipur, India
ORCID ID : 0000-0002-4165-169X
[2]Sir Padampat Singhania University, Udaipur, India
ORCID ID : 0000-0002-8481-2764
[3]Sir Padampat Singhania University, Udaipur, India
ORCID ID : 0000-0001-8062-4144

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Abstract

Leprosy is a persistent infectious illness produced by bacteria called Mycobacterium leprae. Lepra responses and delayed leprosy diagnosis might result in chronic neuritis and eventually disability. This paper aims to classify leprosy patients' Electronic Health Records (EHRs) based on the severity of their diseases as managed at the designated center in India. The health records include demographic information, signs of symptoms, laboratory test results, and clinical notes. The leprosy EHRs are modeled with Systematized Nomenclature of Medicine-Clinical Terms (SNOMED-CT) medical codes. To predict the future clinical events deep learning algorithms using Long short-term memory (LSTM) networks have been validated in the last few years. However, the performance of the LSTM network depends upon the selection of hyperparameters. We propose a novel method of optimizing LSTM parameters using chicken swarm optimization (CHSO) to classify the severity levels of leprosy patients as mild, moderate, or severe cases. Instead of using trial and error-based hyperparameter tuning, the proposed CHSO-LSTM model provides the best fittest value of hyperparameters to increase the accuracy of classification. The result shows that our model outperforms ANN, GRU, LSTM, Bi-LSTM, and Particle Swarm Optimization-based LSTM deep learning models concerning performance matrices Accuracy (ACC) - 99.11%, Precision (PRE) - 99%, Recall (REC) - 99%, F1-Score (F1-SCR) - 99%, Matthew's correlation coefficient (MCC) - 0.9902 and categorical cross-entropy loss (CCE-loss) - 0.0197.

Keywords: *Electronic Health Records, Leprosy, LSTM, Chicken Swarm Optimization, Particle Swarm Optimization, Deep Learning*

Introduction

Deep learning and healthcare data are two major areas of interest for modern data science. Electronic health records (EHRs) are used to maintain healthcare information specific to individual patients. Every time a patient sees their primary care physician, the integrated electronic health record (EHR) is updated with the procedures that the doctor has prescribed or the notes that the doctor has made [4].

The focus of the issue now is on comprehending the data rather than just collecting it. The majority of the EHR data are unstructured, complicated, and heterogeneous, therefore, to uncover hidden knowledge, it must be retrieved and merged in an organized manner. A framework for representation learning called Patient2Vec that uses the attention mechanism and recurrent neural networks to construct a personalized explainable deep illustration of EHR records is proposed in the paper [5].

Leprosy is regarded as a public health issue and is found in more than 120 countries, with 2 lakh fresh cases reported every year, out of which 80% of existences appear in India, Brazil, and Indonesia [1]. The Worldwide Leprosy Report from the World Health Organization published in the year 2021 declares that all country programs should strive toward these four primary objectives. (i) Zero leprosy roadmap in all prevalent countries; (ii) intensify prevention of additionally combined recognition of active cases; (iii) control the problems of leprosy and prevent the emergence of new disabilities; and (iv) eliminate stigma and promote the recognition of human rights. India is the nation with the major global leprosy rate. (58% of new cases), with 114451 new cases detected in 2019–20 and 75394 new cases in 2020–21[2]. Delays in diagnosing leprosy and lepra responses, which cause prolonged neuritis and eventually disability, are included with the main causes of the growth in disability. To encourage self-reporting, early identification, and appropriate treatment of the illness it is required to have awareness of leprosy's signs, symptoms, and reactions among medical personnel.

The goal of the intended innovation is to determine the severity of different leprosy cases in the early stages. Several factors will be examined from the leprosy patients' electronic health records to predict the severity associated with leprosy patients. The demographic data, diagnosis, laboratory test results (skin smear test), and clinical notes are all included in the medical records and collected at the well-known referral center located in India.

The major contribution of the work is as follows.

- Development of CHSO-LSTM, a new LSM model for severity classification of leprosy cases by optimizing hyperparameters using the Chicken swarm optimization technique.
- The architecture of CHSO-LSTM consists of a linear stack of sequential layers (input layers and hidden layers) to learn the features trailed by a dense layer including the last layer's SoftMax activation function finally provides class labels of severity. The hyperparameters involving the number of hidden layers, epochs, learning rate have been set for the proposed LSTM structure optimized by Chicken Swarm optimization.
- The classification layer provides multiclass labels of the severity of leprosy patients as Mild (0), Moderate (1), and severe (2) cases.
- The performance parameters like accuracy, precision, recall, F1-scores, Matthew's correlation coefficient, and categorical cross-entropy loss of the suggested model are compared with various present deep learning models used for electronic health record analysis.

The remaining portion of the document is structured as given next: The significant literature is covered in Section 2 along with several cutting-edge ML and DL methods for leprosy and EHR analysis. In Section 3, the methodology used for the proposed work is elaborated in detail, and the results and findings are shown in Section 4. The Section 5 has outlined conclusion of the study.

1. Related Work

During current years, Leprosy diagnosis assisted by AI is continuously changing, and this field of study is still in its beginnings. Cutting-edge ML methods are used for the multiclass classification of leprosy cases. Deep learning models are developed to identify leprosy skin lesions.[3]

In a study [8] There are various AI models, evaluating pictures and metadata separately and in grouping, using this dataset to see if an AI system included with CNN could aid in leprosy detection. According to AI modeling, the most significant clinical indicators of leprosy include loss of thermal sensitivity, paresthesia in the feet, count of lesions, nodules and reactions, gender, and scaling surface and pruritus. An improved area under curve (AUC) and a high classification accuracy were obtained for leprosy diagnosis using elastic-net logistic regression.

Applying gene appearance records from RNA-Seq and RT-qPCR, Random Forest, an ML-based technique [9], has been used to choose gene characteristics and create a model to predict leprosy advancement. The cases of paucibacillary or multibacillary leprosy have been accurately classified by the RF model in the suggested app [10] by looking for trends in cases of leprosy that were documented in the SINAN database.

A decision tree-based approach was used to track household contacts and categorize clinical types of leprosy (PB/MB) using binary classification [7]. Multi-drug therapy is one of the most effective therapies for this illness, according to their studies. The course of treatment ranges from six to twelve months and has been detected based on the type (PB or MB) and intensity of leprosy.[6]

The EHRs are utilized to update and automate clinical systems workflow. EHRs can be classified according to the following traits: (i) Clinical notes are not included in structured EHRs (ii) Semi-structured EHRs that include clinical notes attached, and (iii) an unstructured EHR comprehensive system. [11] The study [13] depicts various deep learning-based architectures for outcome predictions, EHR representation, and Hospital re-admission prediction.

Medical and healthcare workers, including doctors and nurses, can refer to medical diseases and symptoms using SNOMED CT as a standard, which removes any confusion that may arise from the usage of regional or colloquial words. The code is incorporated with electronic health records are used to develop the opportunities for efficient utilization and guarantee higher-value documents that promote endurance of care, hence facilitating higher-worth health care delivery [12].

2. Proposed Work

In our study, we proposed a framework that makes use of the dataset including electronic health records of leprosy patients to detect the severity of the case. We have developed a thorough strategy that includes several important steps. First, a web-based patient history form is developed to collect EHR data. In the next step, a rule-based technique is used to generate the severity score for each patient, providing a normalized score for each of the features connected to the patient record with the help of expert doctors. To reduce model overfitting and improve model interpretability random forest-based feature section method was deployed and important features from the EHRs were selected. At the core of our approach, we use cutting-edge deep learning models along through standard machine learning models. [13,14].

Further, we have made innovative advancements to the LSTM deep learning architecture by incorporating chicken swarm optimization into hypermeter optimization to increase model performance. The proposed optimization approach for the LSTM model is also differentiated with the Particle Swarm Optimization-based LSTM model. Figure 1 displays the general architecture of the system proposed in our study. The comprehensive approach offers a strong foundation for the reliable and accurate classification of the severity level of leprosy patients, and it has the potential to have an extensive influence on patient care and medical decision support systems.

3.1 Leprosy EHR Data Collection

Doctors treating patients with leprosy can enter details about the patient's demographic information, allergies, signs and symptoms, leprosy forms, the grade of disability, number of nerves impacted, skin smear test results, prescription drugs, and much more into a web-based electronic health record system developed in our study. The web-based patient history form was used to gather data, which was then saved as a.csv file. Several parameters are examined once some domain knowledge has been acquired to select features from the EHR dataset. These features are used to analyze the severity level of the leprosy patient.

3.2 EDA of Leprosy EHRs

The leprosy EHRs contain 3035 individual patient records with 12 attributes**.** Systemized Nomenclature of Medicine - Clinical Terms (SNOMED-CT) terms used to prepare note of different forms of leprosy in this study. Table 1 illustrates the overall understanding of EHR data. The outcome of the skin smear test is recorded as MI and BI values. The disability grade distribution of leprosy patients across all severity levels in the EHRs is displayed in Figure 2 (a). Figure 2 (b) indicates the distribution of mild, moderate, and severe cases in the leprosy EHRs.

3.2.1 Generation of Severity score

To ensure that every patient receives a consistent score, these attribute values need to be normalized so that they fall within a predefined range. This was accomplished by creating detailed guidelines for every attribute. The mean of all the normalized attribute estimates for a given record was used to get the severity score for that patient entry. Labels—Mild, Moderate, and Severe—are then applied to each entry based on the previously mentioned score. For each feature presented in each entry of the dataset, the corresponding score of the feature is calculated and expressed as a set of functions for EHRs Dataset D, as shown below in Equation (1).

h(D) = {h(D1),h(D2),…, h(Dt),…,h(D12)} (1)

The severity score stated as in Equation 2

$$Sj = \sum_{i=1}^{n} \frac{h(Di)}{c} \quad (2)$$

Here c is the count when the corresponding *h(Di)* value is not zero, n is the number of features and j denotes record ID.

Lastly, each patient's EHR record has the score added to the EHR dataset and assigned a mild, moderate, or severe classification based on the conditions if $Sj \leq 33$ the record is labeled as mild, else if $33 < Sj \leq 66$ it is considered as moderate and if $Sj > 66$ the case is labeled as severe.

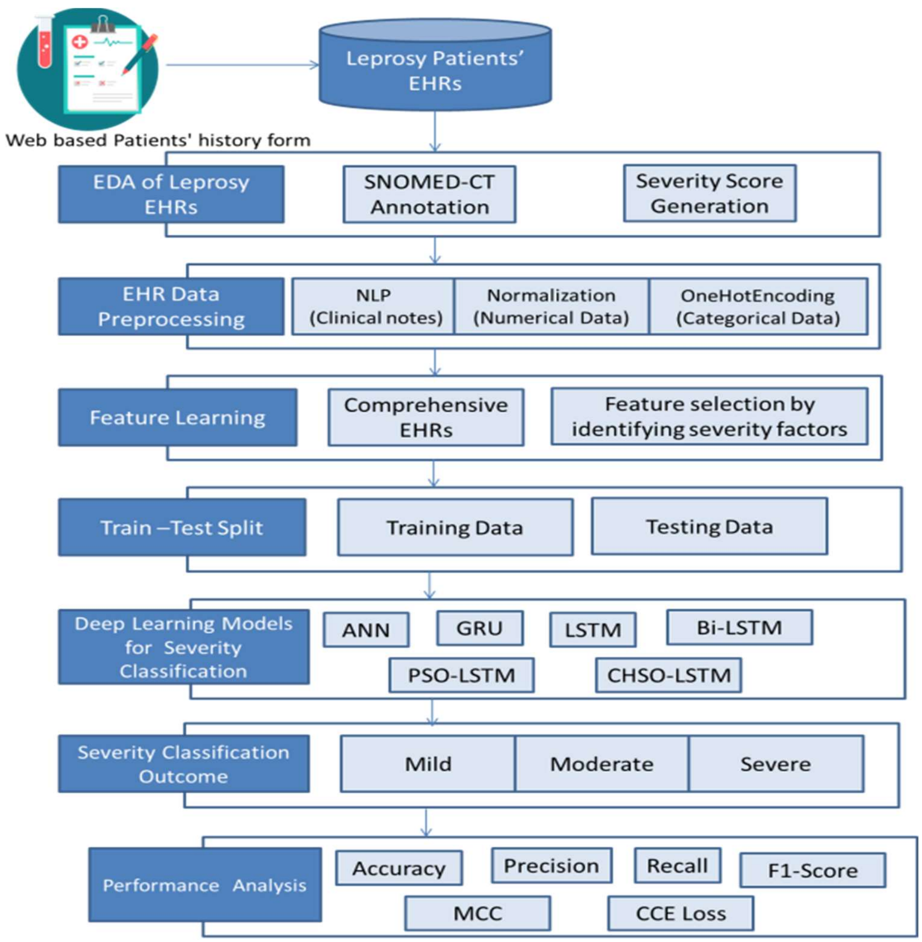


Figure 1. System Architecture

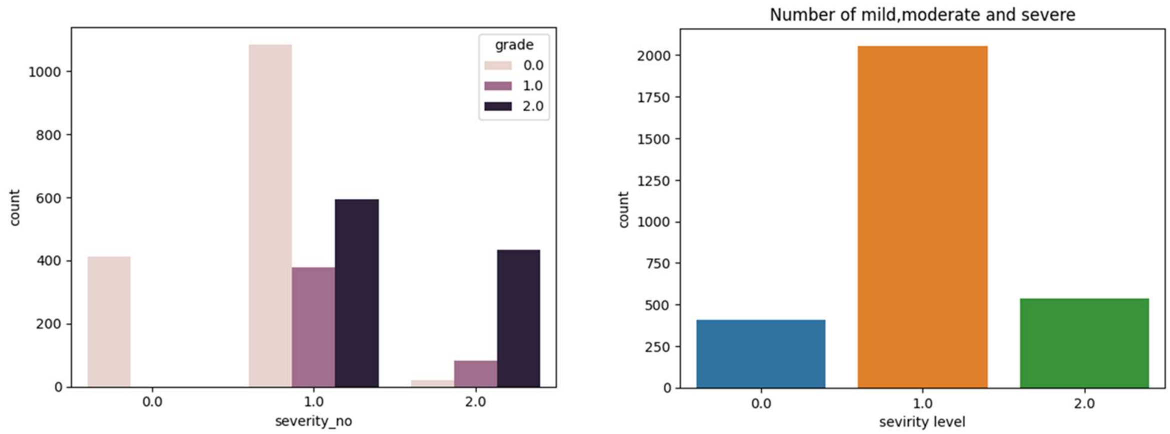


Figure 2 (a) Disability grades (b) Mild , Moderate and Severe case

Table 1 Understanding EHR Data

Pid	Patient ID	Numerical
MI	Morphological Index	Numerical
BI	Bacterial index	Numerical
Nerves	Number of nerves affected	Numerical
Age	Age of patient	Numerical
Disability Grade	Grade 0 - Absence of disability Grade 1- Loss of protective sensibility Grade 2- Presence of deformities	Categorical
Type	Type of Leprosy (PB/MB)	Categorical
Sub_Type	Clinical Classification (BB/BL/TT/BT/LL)	Categorical
SCTID	SNOMED-CT CODE	Numerical
Gender	Gender of patient	Categorical
Score	Calculated severity score	Numerical
Severity_Level	0- Mild 1- Moderate 2- Severe	Categorical

3.2.2 EHR data preprocessing

In the patient history form symptoms and skin lesion assessments are recorded in the text format. We applied basic NLP jobs like stop word removal, lemmatization, and tokenization to preprocess the text information. The rule-based technique has been deployed to identify the general type of leprosy and the clinical classification of the leprosy sub-types. Table 2 shows the symptoms for the different types of leprosy cases and their respective standardized SNOMED-CT codes. After identifying the type of leprosy, it is recorded in the EHRs. There are two categories for the features: numerical and categorical. The numerical data are scaled using normalization, and OneHotEncoder encodes the categorical values. 30% percent of the EHRs are utilised to estimate the trained model's performance, however, the residual 70% percent is applied for training the model.

Table 2 Symptoms and Leprosy Classification

Leprosy Classification	**SCTID**	**Symptoms**
Paucibacillary Leprosy (PB)	416483009	1 to 5 asymmetrical skin lesions with definite loss of sensation and only 1 nerve involved.
Multibacillary Leprosy (MB)	416257001	More than 5 symmetrical skin lesions by indefinite loss of sensation and 2 or more nerves involved.
Tuberculoid Leprosy (TT)	70143003	1 to 3 big-sized asymmetrical skin patches with a clear border and with the presence of anesthesia.
Borderline Tuberculoid (BT)	240402003	More than 4 big-sized asymmetrical patches with clear borders and anesthetic conditions.
Mid-Borderline (BB)	400154003	multiple medium to small-sized patches with clear borders at some places and toward a symmetrical shape
Borderline Lepromatous (BL)	240403008	multiple small symmetrical skin patches with slightly ill-defined borders and no loss of sensation
Lepromatous Leprosy (LL)	21560005	multiple small symmetrical patches with ill-defined borders and no anesthetic conditions

3.3 Deep Learning Models for Severity Classification

Deep learning methods and tools are being integrated into EHR systems to offer profound insights into health outcomes, by making use of their distinctive methods for pattern identification and data processing [24]. The ANN is employed with multiple layers of neurons including input, for giving data; hidden layers, for mining patterns and handling maximum core processing; and an output layer, that generates and shows the ultimate network yields [25]. The Gated recurrent unit (GRU) was applied for classification tasks as it can perform better in smaller EHR datasets [26].In our study, we applied sequential RNN with GRU 32-cell layers with 6 hidden dense layers having an output layer with 3 units and a sigmoid activation function. Further, in the study LSTM and Bidirectional LSTM (Bi-LSTM) deep learning networks are utilized for severity classification. The models were developed by 32 LSTM / Bi-LSTM units, 64 hidden layers, and an output layer with 3 units and sigmoid activation. Adam optimization and the categorical cross-entropy loss function have been applied for model compilation. Finally, models are trained with 50 epochs with 16 batch sizes.

3.4 PSO- LSTM Model for Severity Classification

The Particle Swarm Optimization (PSO) algorithm includes updating velocity of partcles by finding the best personal position and best global position by particle [14]. The are d dimensions assigned as the search space, vector D can be used to describe the particle's recent position in the search space as shown in Equation (3).

$D = (D_1, D_2, D_3, \ldots\ldots. D_d)$. (3)

The particle's velocity is defined by vector V having d dimensions as shown in (4)

$V = (V_1, V_2, V3\ldots.V_d)$. (4)

The historical optimal position of the n^{th} particle is defined as
$P_H = (P_1, P_2\ldots, Pd)$, and P_U is the defined particle's universal optimal position. The particles iteratively search their P_H and P_U by applying equations of velocity and position shown below.

$$V_i^{n+1} = W\, V_i^n + C1 * R1\, (P_i^n + D_i^n) + C2 * R2(P_U^n - D_i^n) \quad (5)$$

$$Di^{\,n+1} = Di^{\,n} + V_i^{n+1} \quad (6)$$

Equation (5) shows the velocity of the particle having index i in iteration (n+1) by calculating the sum of parameters including the product of the velocity of the nth generation particles and the inertia weight W, after that it describes the own optimal position multiplied by a random number R1 having uniform distribution in [0,1] and Constant C1 which is a local learning factor. Finally, it is added by a universal optimal solution with random numbers R2 and C2 which is a global learning factor. The position of the i^{th} particle in $(n+1)^{th}$ iteration is updated by adding position at n^{th} iteration with velocity derived in equation (5) is shown in Equation (6).
In our study, we experimented with Particle Swarm Optimization with the prediction model including LSTM network [15]. Wherein, An LSTM network prediction model is developed, and optimization of hyperparameters is done by the PSO technique. The model is then utilized to forecast the patient's severity as mild, moderate, and severe. Algorithm 1 illustrates the process of modeling and optimization.

Algorithm 1: PSO-LSTM for predicting the severity of leprosy patients from Electronic Health Records.

Input: EHR dataset of Leprosy patient EDS, Let X, be the features set provided as input to the LSTM model. Let Y be the predicted severity class label for the relevant given feature record.

Output: Classification of severity as mild, moderate, or severe.

1. Split the Input feature set X and Output set Y into training and testing sets.
2. Initialize parameters provided as input to LSTM model.
3. Initialize PSO parameters as num_particles, max_iteration, C1, C2, and inertia Weight W.
4. While the iteration < = max_iteration do
5. For each particle in the swarm
   a. Evaluate the fitness function.
   b. Update the historical optimal position P_H and universal optimal position P_U according to fitness.
   c. Calculate the velocity of the particle as referred to in Equation (6)
   d. Calculate the position of the particle as referred to Equation (7)
6. End For
7. End While.
8. Obtain the Global best parameters of PSO.
9. For each patient record (X, Y) Є EDS dataset,
   a. Provide the training input feature set X to the LSTM network.
   b. Train the LSTM model with global optimized parameters by PSO.
   c. Get the predicted output Y as the severity class label.
10. End For
11. Get the comparision of actual Y values and predicted Y values as severity levels mild, moderate, and severe.
12. Evaluate performance metrics containing Accuracy, Recall, F1-score, Precision, and MCC parameters.
13. End.

3.5 Proposed CHSO-LSTM Model for Severity Classification

X. Meng, et. al [16] created a swarm intelligence method called Chicken Swarm Optimization (CHSO). The chickens' activities were selected with the Chicken Swarm optimization algorithm by the given conditions as follows.

(i) Within the swarm of chickens, there are multiple groups. The group consists of a leading rooster, a few hens, and chicks.
(ii) The devision of the swarm of chickens into multiple groups and identification of the roosters, hens, and chicks., will be determined by their fitness ratings. Each hen would serve as the leader rooster in a group and be considered the best in many fitness parameters. The hens with the lowest multiple fitness levels would be referred to as chicks.
(iii) The hens arbitrarily opt for the group they will stay in. Additionally, the hens' and chicks' mother-child bonds are developed at random.
(iv) In a cluster, the mother-child bond, the control connection, and the ranked order will all remain the same.

(v) Chickens trail their fellow roosters in search of food, yet they can prevent the others from consuming their food. Expect nice food to be randomly stolen from chicks that have already been searched by others. In and around their mother hen, the chicks go for food hunting.

There are N number of chickens denoted by their positions during time step t in a search space with D-dimensions. The position is denoted as $P_{i,j}^{t}$ where i ∈ [1,…,N] and j ∈ [1,…,D]. Higher-fitness roosters are given an advantage over lower-fitness roosters when it comes to food access. Equation 7 shows the formulation for the rooster position where $R(0,\sigma^2)$ denotes the Gaussian distribution having mean value of 0 and the standard deviation is indicated in Equation 8 as σ^2 .

$$P_{i,j}^{t+1} = P_{i,j}^{t} * \left(1 + R(0,\sigma^2)\right) \quad (7)$$

$$\sigma^2 = \begin{cases} 1, \; if \quad fi < fr \\ exp\left(\frac{(fr-fi)}{abs(fi)+con}\right), otherwise \end{cases} \quad (8)$$

Here, $fr = fitness\ value\ of\ rooster$
$fi = fitness\ value\ of\ chickens$
$con = constant\ value\ added\ to\ avoid\ divide\ by\ zero\ error$

Hens follow the roosters in their group when they are looking for food, and they will occasionally take their favorite food from other chickens. The position for hens is formulated in Eq. (9)

$$P_{i,j}^{t+1} = P_{i,j}^{t} + V1 * R1 * \left(P_{r1,j}^{t} - P_{i,j}^{t}\right) + V2 * R1 * \left(P_{r2,j}^{t} - P_{i,j}^{t}\right) \quad (9)$$

Here,

$$V1 = ex\,p\left(\frac{(fi-fr1)}{abs(fi)+c}\right) \quad (10)$$

$$V2 = exp\ exp\ (fr2 - fi) \quad (11)$$

Where r1 is the index of the rooster and r2 is an index of chicken chosen from swarm hen or rooster such that r1 ≠ r2. R1 is a random number between 0 to 1. For every group, there will be a different rooster fitness value. The fitness values of roosters are denoted by $fr1\ and\ fr2$. The chicks will gather around their mother hen as they look for food. The position for chicks is represented numerically in the Eq. (12)

$$P_{i,j}^{t+1} = P_{i,j}^{t} + CL * \left(P_{m,j}^{t} - P_{i,j}^{t}\right) \quad (12)$$

Where $P_{m,j}^{t}$ is the position of ith chick mother. The factor *CL* is a number randomly selected from the range [0,2].

In our study, we proposed Chicken Swarm Optimized Long short-term memory model called CHSO-LSTM. The CHSO method has been applied to best adjust the LSTM model's hyperparameters, which increases the accuracy of the model. The CHSO approach's high parallelism and simplicity make it better than other optimization strategies applied in the field of healthcare [17-20]. Fig 1 depicts the flowchart for the proposed CHSO-LSTM algorithm. The model is finally applied to classify the severity of the leprosy patient's case as mild, moderate, and severe. The working of the LSTM model and optimization process is demonstrated in algorithm 2.

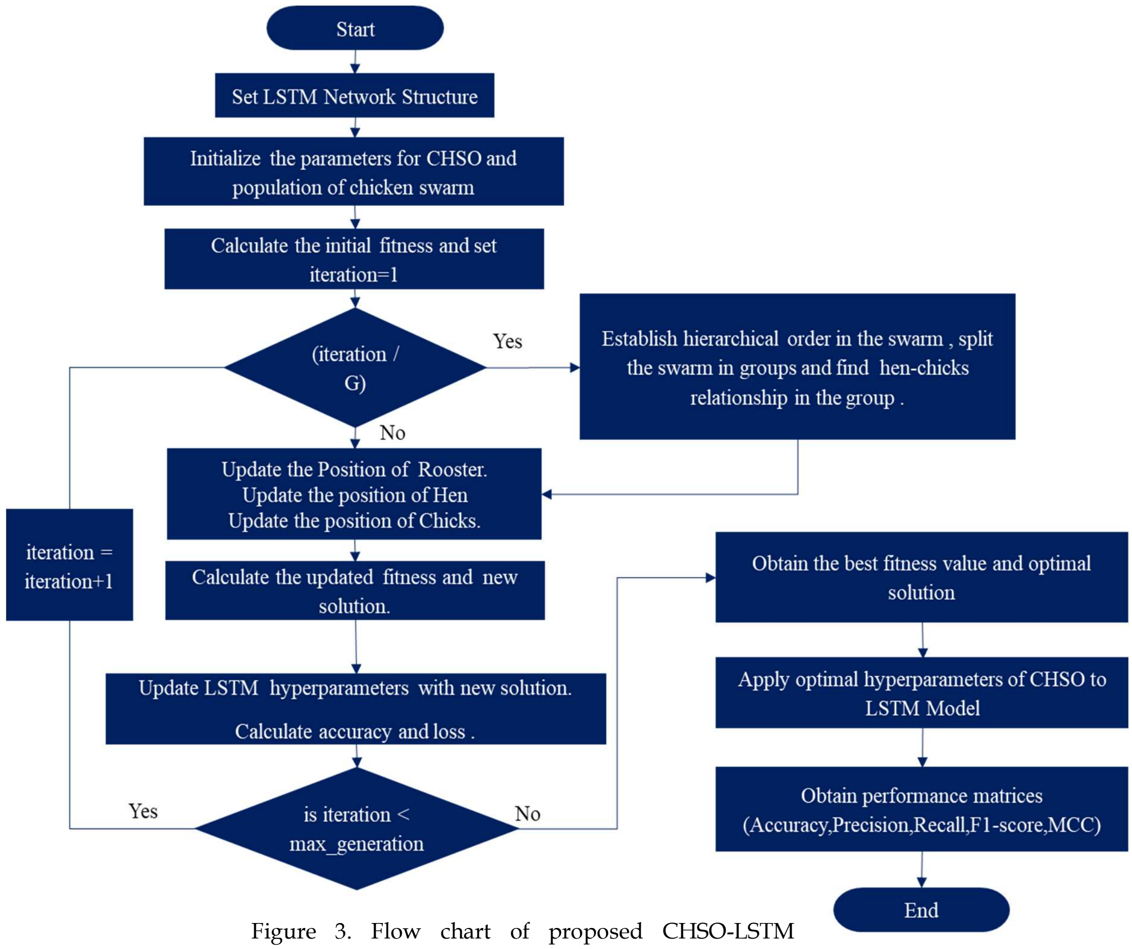


Figure 3. Flow chart of proposed CHSO-LSTM

Algorithm 2: Proposed CHSO-LSTM for severity classification of leprosy patients from Electronic Health Records.

Input: EHR dataset of Leprosy patient EDS, Let X, be the features set provided as input to the model. Let Y be the predicted severity class label for the relevant given feature record.
Output: Classification of severity as mild, moderate, or severe.

1. Split the Input feature set X and Output set Y set into train_x, train_y, and test_x, test_y.
2. Initialize the structure of the LSTM model by setting parameters.
3. Initialize CHSO parameters and N number of chicken population as max_generation, self_update_time.
4. Evaluate initial fitness value and set iteration=1
5. Load the training dataset.
6. While (iteration < max_generation)
   a. if (iteration % self_update_time == 0)
   b. Establish hierarchical order in the swarm by ranking the fitness measures of chickens, split swarm population into collections, and find hen-chick relationships in the collection.
   c. End if.
   d. For i in range (1,N)
   e. if i = Rooster
      Obtain the new position of the Rooster using.
      Eq. (7)
      End if.
   f. if i= Hen
      Obtain the new position of the Hen using.
      Eq. (9)

      End if.
   g. if i=chick

Obtain the new position of the Chick using.
Eq. (12)
End if.

h. Evaluate new solution having fitness value improved than the prior one.
i. End For.

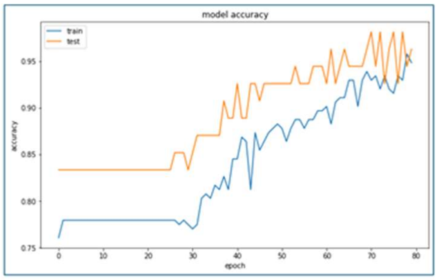
7. End While.
8. Find the best fitness value and optimal chicken solution.
9. Initialize LSTM structure with hyperparameters optimized by CHSO.
10. Train the LSTM model with train_x, train_y, and CHSO solution parameters.
11. Obtain the predicted output Y as severity class label.
12. Evaluate the matrices of the CHSO-LSTM classification model for test_x , test_y data.
13. End.

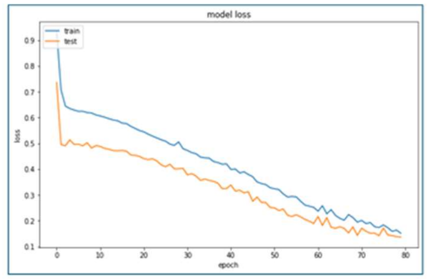
3. Result Analysis

The performance analysis of severity detection of leprosy patients' utilizing the proposed deep learning model named Chicken Swam optimized long short-term memory (CHSO-LSTM) is covered at this segment. Patients with leprosy have their electronic health records gathered at an Indian leprosy care center. There are 3035 records of EHRs collected using a web-based patient record system. The records are transformed into a .csv file by merging various fields of the database. There are 14 attributes included in initial leprosy EHRs. It is reduced to 12 features by employing a random forest-based feature selection method, in the proposed prediction method.

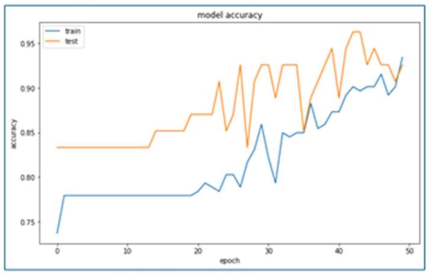
Table 3. Comparative analysis of Deep learning models

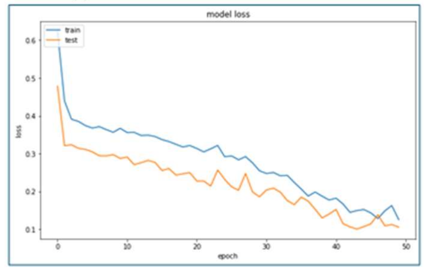
Deep Learning Models	*ACC*	*PRE*	*REC*	*F1-Score*	*MCC*	*CCE-Loss*
ANN	96.30%	94%	94%	93%	0.8876	0.1513
GRU	93.59%	88%	93%	90%	0.9249	0.2402
LSTM	98.33%	98%	97%	97%	0.9768	0.1165
Bi-LSTM	97.43%	97%	97%	97%	0.9660	0.1255
PSO-LSTM	98.89%	98%	98%	98%	0.9838	0.0302
Proposed CHSO-LSTM	99.11%	99%	99%	99%	0.9902	0.0197



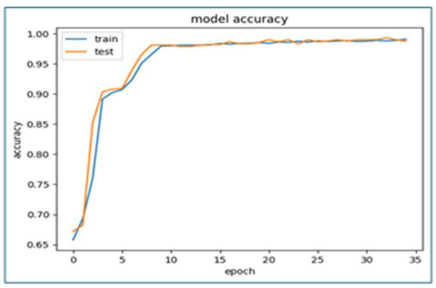


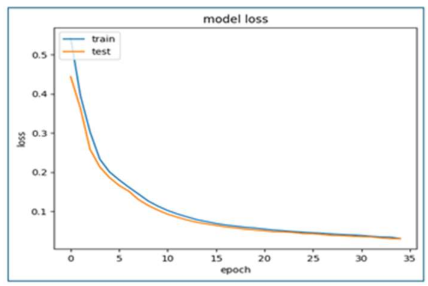
(a) LSTM Model Accuracy curve (b) LSTM Model loss curve



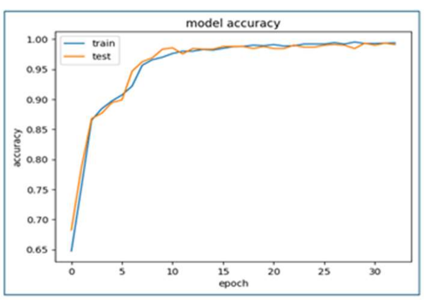


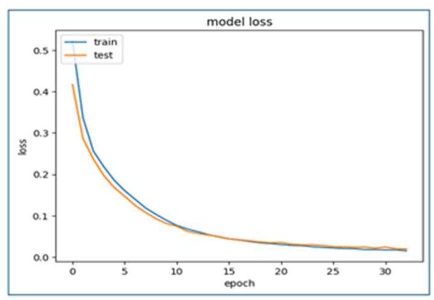
(c) Bi-LSTM Model Accuracy curve (d) Bi-LSTM Model loss curve





(e) PSO-LSTM Model accuracy curve (f) PSO-LSTM Model loss curve



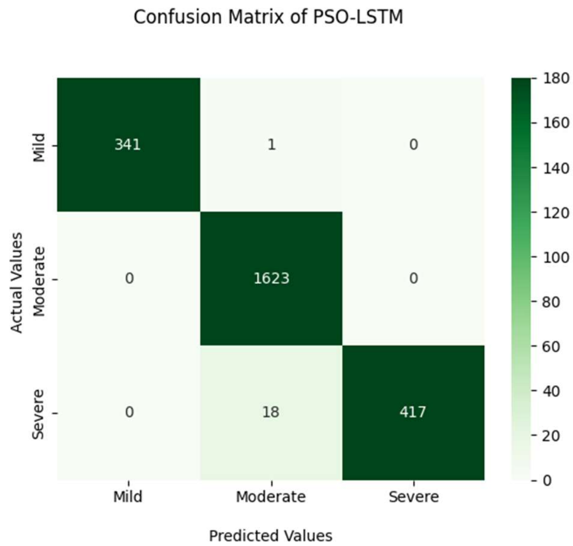


(h) CHSO-LSTM Model accuracy curve (i) CHSO-LSTM Model loss curve

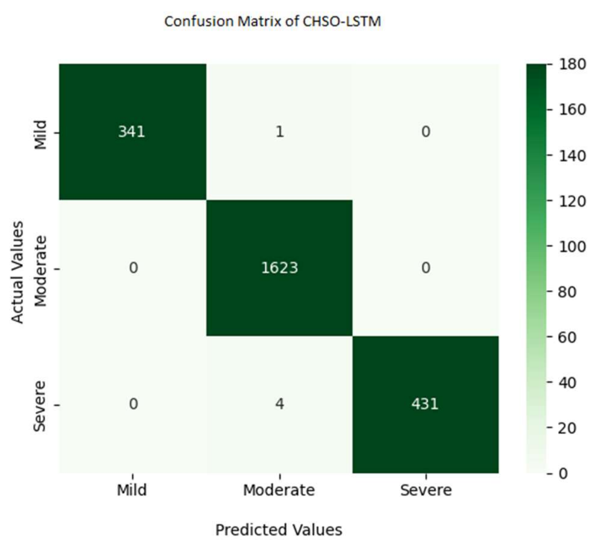
Several deep learning models are deployed to compare the proposed model's performance that is currently in use for classification, including Artificial Neural network (ANN), Gated Recurrent Unit (GRU), Long Short-Term Memory (LSTM), and Bi-directional LSTM (Bi-LSTM) Classifiers. The analysis of their performance matrices is shown in Table 3. The following section discusses the specific performance matrices.

4.1 Performance Matrices

The classifiers' performance is assessed using the evaluation metrics that are produced.[21]. Metrics like F1-score, recall/sensitivity, precision, and accuracy are some of the ones used to assess a classifier's effectiveness. Equation 13 illustrates both the total sample size and the proportion of accurate predictions as the accuracy of the classifier.



$$\boldsymbol{Accuracy\ (ACC)} = \frac{\boldsymbol{TRP + TRN}}{\boldsymbol{S}} \qquad (13)$$



Precision is the classifier's ability to correctly classify a sample with all other and incorrectly placed samples in that class, which is computed using Equation 14.

$$\boldsymbol{Precision\ (PRE)} = \frac{\boldsymbol{TRP}}{\boldsymbol{TRP+FAP}} \qquad (14)$$

The likelihood that a sample will fall into a class is determined by Sensitivity or Recall as shown in Equation 15.

$$\boldsymbol{Sensitivity\ or\ Recall(REC)} = \frac{\boldsymbol{TRP}}{\boldsymbol{TRP+FAN}} \qquad (15)$$

Striking a balance between recall and precision is necessary, and it can be derived from F1-Score as shown in Equation 16.

$$\boldsymbol{F1 - Score\ (F1 - SCR)} = \frac{\boldsymbol{TRP}}{\boldsymbol{TRP+FAN}} \qquad (16)$$

Here, S =Total No. of samples

TRP indicates overall no. of True Positives.

TRN indicates overall no. of True Negatives.
FAP indicates overall no. of False Positives.
FAN indicates overall no. of False Negatives

The quality of multiclass classifications is assessed using the Matthews correlation coefficient. Since it accounts for both true and false positives in addition to negatives, it is widely recognized as a fair measure that may be applied even when the sizes of the classes differ substantially. [22]. Equation 17 shows the mathematical formulation of MCC.

$$MCC = \frac{c \times s - \sum_k^K p_k \times t_k}{\sqrt{(s^2 - \sum_k^K p_k^2) \times (s^2 - \sum_k^K t_k^2)}} \qquad (17)$$

In multiclass classification, categorical cross-entropy loss is quite helpful, especially when analyzing the results of the LSTM networks that use the SoftMax function [23], which is frequently used in deep learning models. The difference between two probability distributions is measured by this loss function, which indicates how well the model predicts the actual results.

The formula for CCE loss is derived in Equation 18.

$$CCE\text{-}Loss = -\sum_{i=1}^{i=k} Yi\_true * log\ (Yi\_predicted) \qquad (18)$$

4.2 Results and Findings

The training-test splits for the leprosy patients' electronic health records dataset is 70%-30%. The whole data set was either utilised for testing or for training. Testing sets and training sets do not intersect in terms of subjects or patients. Instead, the sets represent distinct populations. The accuracy and loss comparison graph for each LSTM classification model used in our investigation is displayed in Figure 4. It displays the loss curve and training and validation accuracy curve for the LSTM, Bi-LSTM, PSO-LSTM, and proposed CHSO-LSTM.

The performance measures, incorporating accuracy, precision, recall, and F1-score, have been evaluated using the confusion matrix. It makes it possible to assess a model's accuracy for data classification Here k is the number of classes. In the study k = 3 (mild, moderate, severe), *c* is the accurately predicted samples, *pk* is the quantity of times class k was predicted, *tk* is the quantity of times class k existed.and the ability to prevent false positives and false negatives in specifics, that is crucial for decision support and addressing challenges. Figure 5 and Figure 6 depict the confusion matrix of best performing models PSO-LSTM model and proposed CHSO-LSTM Model respectively. It is observed that in both models predicted values of mild and moderate cases are same, but the proposed model could predict a greater number of true positive severe cases, hence increased accuracy.

It is clear from looking at Figure 4, Figure 6, and Table 3 that the proposed CHSO-LSTM classification model imroved performance than the traditional deep learning models with highest value throughout all performance parameters. On the other hand, the more trustworthy statistical rate known as the Matthews correlation coefficient (MCC) obtained a high value for when the prediction was successful across all categories of confusion matrix. It shows that the MCC value 0.9902 is towards the +1 value which is nearly perfect classification.

The number of epochs required to train the model optimized by proposed CHSO-LSTM, are less compared to all other models as shown in figure 4. There are 30 epochs required, which take less time to train the model. The model optimization procedure also decides shape of the LSTM network by optimizing the total hidden layers and units in each layer. The learning rate remained at 0.01. Particularly, The Chicken swarm optimized LSTM methodology is the best-performing algorithm out of all those tested, proving its efficacy and robustness in multiclass severity classification of leprosy EHRs.

4. Conclusion

The unclear and inconsistent information provided in the leprosy EHRs dataset is too difficult for the current algorithms to handle. This paper intends to process semi-structured leprosy EHR data which includes text information as symptoms, skin lesion assessment, numerical records like age, skin smear test results, number of nerves affected, and categorical values like the type of leprosy, disability grade, gender, etc. recorded by doctors in the web-based EHRs system developed. Deep learning-based classification methods are employed in this work to classify leprosy patient cases into three severity levels. The severity score for every patient is generated using a rule-based methodology and a normalized score is calculated for each component related to the patient record**.** The performance of LSTM networks used in the study is solely determined by their hyperparameters, which are crucial for multi-class classification tasks. Therefore, we suggested Chicken swarm intelligenc**e,** which enhances the performance, by finetuning hyperparameters in the best possible way. Insightful findings from our performance analysis show that the suggested CHSO-LSTM model performed better than alternative models**.** This highlights the potential for our innovative technique to improve the accuracy of severity classification in leprosy cases, ultimately leading to better medical treatment and early diagnosis.

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