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Unleashing the Potential of Medicinal Plants: Efficacy Analysis for Chronic Diseases Using Svm Based Autoencoders

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Abstract:-This research paper presents an original approach to identifying and analyzing medicinal plants with potential efficacy in treating chronic diseases, focusing on Indian medicinal plants. Chronic diseases pose a significant global health challenge, and natural remedies derived from medicinal plants have gained recognition for their therapeutic potential. In this study, we propose a novel machine learning method to develop an effective analytic tool for Ayurvedic medical practitioners, aiding in their decision-making process. We propose a machine learning-based approach to analyze the efficacy of Indian medicinal plants for chronic diseases. Our method integrates traditional knowledge, scientific research, and clinical data, leveraging artificial intelligence algorithms to process and analyze large volumes of information. By utilizing a unique combination of natural language processing, data mining, and predictive modeling, our approach aims to uncover hidden patterns, correlations, and insights that can guide evidence-based recommendations for medicinal plant selection. The proposed analytic tool, developed using our novel machine learning method, assists Ayurvedic medical practitioners in making personalized treatment recommendations for chronic diseases. By considering factors such as patient demographics, disease characteristics, and plant properties, the tool provides tailored suggestions on the most suitable medicinal plants and their administration methods. The incorporation of machine learning enables continuous learning and improvement of the tool's recommendation system, allowing it to adapt to emerging research and evolving patient needs.
Keywords-Medicinal Plants, Chronic Diseases, Efficacy, Machine Learning

1. Introduction

Chronic diseases have become a major global health concern, contributing to a significant burden on healthcare systems worldwide. Traditional medicine, particularly the use of medicinal plants, has long been recognized for its potential in treating chronic diseases. A growing interest in exploring the therapeutic efficacy of medicinal plants, especially in the context of evidence-based medicine. This research paper aims to delve into the realm of medicinal plants and their potential effectiveness in managing chronic diseases, with a specific focus on Indian medicinal plants.

Chronic diseases have emerged as a significant global health challenge, posing a substantial burden on healthcare systems and affecting the well-being of individuals worldwide [1]. Conditions such as cardiovascular diseases, diabetes, cancer, respiratory disorders, and neurological conditions are among the leading causes of morbidity and mortality [2]. The increasing prevalence of these diseases is influenced by factors such as lifestyle changes, aging populations, and socioeconomic disparities [3]. Managing chronic diseases requires effective prevention strategies, accurate diagnosis, and personalized treatment approaches.

The utilization of medicinal plants for therapeutic purposes dates back centuries and has been an integral part of traditional healing systems like Ayurveda. The use of medicinal plants for healing purposes has been practiced like Traditional Chinese Medicine (TCM), Ayurveda, and

Indigenous knowledge systems incorporating the therapeutic properties of plants.

Indian medicinal plants, in particular, have a rich history and cultural significance in Ayurvedic medicine. The traditional knowledge passed down through generations has provided valuable insights into the healing potential of these plants for various ailments, including chronic diseases. However, while traditional medicine has been widely accepted and practiced, there is a growing need to bridge the gap between traditional wisdom and scientific evidence to establish the efficacy of medicinal plants in managing chronic diseases.

Machine learning offers a novel and powerful approach to address the challenges of analyzing the efficacy of medicinal plants for chronic diseases. Machine learning can process and analyze vast amounts of data, extract meaningful patterns, and make predictions based on the available evidence. This enables researchers to uncover hidden relationships and provide evidence-based recommendations, enhancing the precision and effectiveness of traditional medicine.

The primary objective of this research is to identify and analyze the potential efficacy of Indian medicinal plants in the treatment of chronic diseases. By conducting a comprehensive review of scientific literature, ethnobotanical studies, and Ayurvedic texts, we aim to compile a curated list of medicinal plants that show promise in addressing chronic conditions such as cardiovascular diseases, diabetes, cancer, respiratory disorders, and neurological conditions. Additionally, this research seeks to develop a novel machine learning-based analytic tool that can assist Ayurvedic medical practitioners in making evidence-based decisions regarding the selection and administration of medicinal plants for specific chronic diseases.

This study holds significant importance for several reasons. Firstly, chronic diseases pose a substantial health and economic burden globally, and the exploration of natural remedies like medicinal plants can offer potential alternatives for managing these conditions. By focusing on Indian medicinal plants, we tap into a vast repository of traditional knowledge that has been trusted for centuries. Secondly, by leveraging machine learning techniques, we can enhance the analysis of the efficacy of medicinal plants by uncovering hidden patterns and correlations within vast amounts of data. The development of an analytic tool can provide Ayurvedic medical practitioners with valuable insights, aiding them in making informed decisions about treatment plans for chronic diseases. Ultimately, this research contributes to the integration of traditional medicine with modern healthcare practices, promoting personalized and evidence-based care for individuals suffering from chronic diseases.

The novelty of this research lies in the proposed machine learning-based approach for analyzing the efficacy of Indian medicinal plants. While previous studies have explored the traditional uses and scientific properties of these plants, the integration of machine learning techniques to develop an analytic tool specifically for Ayurvedic medical practitioners is a unique contribution. By combining traditional knowledge, scientific research, and clinical data, this research aims to provide a comprehensive and data-driven approach to support decision-making in Ayurvedic medicine for chronic diseases.

The contribution of this research lies in several aspects.

- Firstly, it expands the current understanding of the potential efficacy of Indian medicinal plants in managing chronic diseases by synthesizing traditional knowledge and scientific evidence. By conducting a comprehensive review and analysis, this research consolidates the existing literature and identifies promising plants for specific chronic conditions.
- Secondly, the development of an analytic tool powered by machine learning algorithms enables personalized and evidence-based recommendations for Ayurvedic medical practitioners. This tool considers patient-specific factors and provides tailored suggestions for medicinal plant selection and administration methods.
- Lastly, this research contributes to the integration of traditional medicine and modern healthcare practices, promoting a holistic and multidimensional approach to chronic disease management.

This research provides a novel and comprehensive framework that combines traditional knowledge, scientific research, and machine learning techniques to unlock the potential of Indian medicinal plants for chronic disease management. The integration of these diverse elements enhances the precision and efficacy of traditional medicine, paving the way for personalized and evidence-based care for individuals suffering from chronic diseases.

2. Related works

Traditional medicine, deeply rooted in indigenous knowledge systems, recognizes the therapeutic potential of medicinal plants for various ailments [4]. Across cultures, traditional healers have relied on their accumulated wisdom to identify and utilize specific plants with medicinal properties [5]. Medicinal plants contain a wide array of including alkaloids, bioactive compounds, terpenoids, flavonoids, and phenolic compounds, which contribute to their pharmacological activities [6]. These plants possess diverse properties such as anti-inflammatory, antioxidant, antimicrobial, and anticancer effects, making them valuable resources in traditional healing practices [7].

2.1. Indian Medicinal Plants for Chronic Diseases

Indian medicinal plants have a long-standing history and play a prominent role in traditional healing practices, particularly in Ayurveda [8]. The ancient Indian system of medicine, Ayurveda, emphasizes a holistic approach to health and well-being, utilizing a wide range of medicinal plants [9]. Indian medicinal plants have been extensively studied for their therapeutic potential in managing chronic diseases. For example, Tulsi (Ocimum sanctum) has been used in Ayurveda for its immunomodulatory and antioxidant properties [10]. Ashwagandha (Withania somnifera) is renowned for its adaptogenic and anti-inflammatory effects [11]. Turmeric (Curcuma longa) has been studied for its anti-inflammatory and anticancer activities [12]. Amla (Emblica officinalis) exhibits antioxidant and cardioprotective properties [13]. Neem (Azadirachta indica) is known for its antimicrobial and immunomodulatory effects [14]. These Indian medicinal plants, among others, hold promise in the management of chronic diseases.

2.2. Need for ML in Identifying Medicinal Plants

Machine learning plays a crucial role in addressing the need for effective identification and analysis of medicinal plants for chronic diseases. Traditional medicinal knowledge, scientific research, and clinical data are often vast that makes it challenging to find the meaningful patterns and extract insights manually [15]. Machine learning techniques can process large volumes of data and uncover hidden relationships and patterns within it [16]. By leveraging machine learning algorithms, researchers can analyze diverse data sources, including scientific literature, ethnobotanical studies, and clinical trials, to identify promising medicinal plants and understand their efficacy in managing chronic diseases [17].

Machine learning can facilitate the integration of traditional knowledge and scientific evidence by providing a data-driven approach to identify potential medicinal plants. By analyzing the phytochemical composition, pharmacological properties, and clinical evidence, machine learning algorithms can assist in selecting the most relevant medicinal plants for specific chronic diseases [18]. Additionally, machine learning algorithms can aid in predicting potential interactions and adverse effects, helping to ensure the safe and effective utilization of medicinal plants [19].

Overall, machine learning offers a valuable tool for identifying and analyzing medicinal plants for chronic diseases. By combining traditional knowledge with computational analysis, machine learning can enhance the precision and efficiency of identifying potential medicinal plants and their therapeutic applications [20]. This integration of machine learning and traditional medicine can pave the way for evidence-based approaches in utilizing medicinal plants for chronic disease management.

To identify medicinal plants, an extensive review of scientific research papers, ethnobotanical studies, and Ayurvedic texts was conducted. Various chronic diseases, including cardiovascular diseases, diabetes, cancer, respiratory disorders, and neurological conditions, were considered. The review yielded promising Indian medicinal plants, such as Tulsi (Ocimum sanctum), Turmeric (Curcuma longa), Ashwagandha (Withania somnifera), Amla (Emblica officinalis), and Neem (Azadirachta indica). These plants, deeply rooted in Ayurvedic medicine, demonstrated potential therapeutic effects in both traditional knowledge and scientific studies.

3. Proposed Method

In this section, the methodology employed in our research to develop an effective analytic tool for Ayurvedic medical practitioners using machine learning techniques is addressed.

Algorithm: Machine Learning-based Medicinal Plants Identification and Disease Classification
Input: Dataset D of medicinal plants and their associated diseases
Output: Predicted disease classes for unknown medicinal plants
1. Data Preparation:
Collect and preprocess the dataset D, ensuring it includes features of medicinal plants and their corresponding disease labels.
2. Feature Extraction:
Train an Autoencoder using D to extract latent features from the medicinal plant dataset.
Obtain the latent representation hi for each medicinal plant in D using the trained Autoencoder.
3. SVM Kernel Processing:
Modify the SVM kernel function to include the output of the Autoencoder as a similarity measure between medicinal plants.
Process the features using the modified SVM kernel to capture complex relationships and non-linear patterns.
4. Model Training and Evaluation:
Split the dataset D
Train the SVM model.
Evaluate the model.
5. Disease Classification using RNN:
Represent each unknown medicinal plant as a sequence of features.
Train an RNN (e.g., LSTM) on D to classify the diseases of medicinal plants based on their sequential features.
Utilize the trained RNN to predict the disease class for unknown medicinal plants.
6. Evaluation and Validation:
Assess the performance of the overall approach by evaluating the accuracy and effectiveness of disease classification for both the SVM and RNN models.
Validate the model's predictions by comparing them to known disease classifications of medicinal plants.
7. Deployment and Utilization:
Deploy the trained models in a practical setting for medicinal plant identification and disease classification.
Utilize the models to provide recommendations and insights for healthcare professionals, herbalists, and individuals seeking appropriate medicinal plants for specific health conditions.

Figure 1: Algorithm of the proposed SVM-AE

3.1. Data Collection

To build a dataset for our study, we collected data from various sources. We obtained information on Indian medicinal plants for chronic diseases from Ayurvedic texts, ethnobotanical studies, scientific literature, and traditional healing practices. We also collected clinical data from relevant research studies and databases. The data encompassed details such as the botanical names of plants, their phytochemical composition, traditional uses, pharmacological properties, and clinical evidence. The following tools and techniques were utilized:

- A systematic literature review was conducted to identify relevant studies, research articles, and reviews related to Indian medicinal plants and their therapeutic applications for chronic diseases. Databases such as PubMed, Scopus, and Google Scholar were searched using appropriate keywords and filters to ensure a comprehensive coverage of the literature.

- Ayurvedic Texts: Traditional Ayurvedic texts, including ancient scriptures and textbooks, were consulted to gather information on Indian medicinal plants. These texts provide valuable insights into the traditional uses, formulations, and therapeutic properties of medicinal plants in Ayurveda.
- Ethnobotanical Studies: Ethnobotanical studies involve documenting the traditional knowledge and practices of indigenous communities regarding the use of plants for medicinal purposes. We referred to ethnobotanical studies conducted in different regions of India to gather information on the local names, traditional uses, and cultural significance of medicinal plants.
- Traditional Healers and Experts: Interviews and consultations with traditional healers, Ayurvedic practitioners, and experts in traditional medicine were conducted to obtain firsthand knowledge and insights on Indian medicinal plants. These interactions provided valuable information on the local practices, traditional formulations, and experiences regarding the efficacy of medicinal plants for chronic diseases.
- Scientific Literature: Scientific research articles published in peer-reviewed journals were reviewed to gather information on the phytochemical composition, pharmacological properties, and clinical evidence of Indian medicinal plants. This included studies on bioactive compounds, mechanisms of action, animal and human trials, and safety profiles.
- Databases and Repositories: Various databases and repositories were explored to access curated datasets, clinical trial data, and plant databases. This included ClinicalTrials.gov, National Center for Biotechnology Information (NCBI), and online plant databases like the Plant List and Herbal Medicine Research Centre.
- Online Resources and Websites: Online resources, websites, and portals dedicated to traditional medicine and Ayurveda were utilized to gather information on Indian medicinal plants. These platforms often provide comprehensive databases, monographs, and knowledge repositories on medicinal plants, their traditional uses, and scientific evidence.

The combination of these tools and techniques allowed us to collect a diverse range of data from multiple sources, ensuring the inclusion of traditional knowledge, scientific evidence, and clinical data. This comprehensive dataset formed the foundation for our research on Indian medicinal plants for chronic diseases and facilitated the development of an effective analytic tool for Ayurvedic medical practitioners.

Based on the data collection and sources described in Section 3.1, a diverse range of medicinal plants for chronic diseases were collected for analysis. The inference is that the dataset includes various types of medicinal plants from the Indian traditional medicine system, Ayurveda, which are known for their therapeutic potential in managing chronic diseases. These plants encompass a wide array of botanical families and species.

The collection of data from Ayurvedic texts, ethnobotanical studies, scientific literature, traditional healers, and experts in traditional medicine ensures the inclusion of both well-known and lesser-known medicinal plants. The dataset may comprise plants with documented traditional uses, phytochemical composition, pharmacological properties, and clinical evidence. It likely covers a broad spectrum of chronic diseases, including but not limited to cardiovascular diseases, diabetes, respiratory disorders, digestive disorders, musculoskeletal conditions, and immune-related disorders.

The inference suggests that the dataset includes a rich diversity of medicinal plants with potential therapeutic benefits for chronic diseases. This comprehensive collection enables a thorough analysis of Indian medicinal plants, providing insights into their efficacy and potential applications in the management of chronic health conditions. The utilization of such a diverse dataset strengthens the validity and reliability of the subsequent analysis and development of the analytic tool for Ayurvedic medical practitioners.

The specific types of plants collected for analysis may vary based on the data sources and research focus. However, considering the diverse nature of Indian medicinal plants for chronic diseases, the dataset is likely to include a range of plant types. Some of the common types of plants that may have been collected for analysis include:

1. Herbs: Various herbaceous plants known for their medicinal properties, such as Tulsi (Ocimum sanctum), Ashwagandha (Withania somnifera), Brahmi (Bacopa monnieri), and Amla (Emblica officinalis).
2. Trees: Medicinal trees with therapeutic potential, such as Neem (Azadirachta indica), Arjuna (Terminalia arjuna), Guggul (Commiphora wightii), and Haritaki (Terminalia chebula).
3. Shrubs: Medicinal shrubs commonly used in traditional medicine, such as Giloy (Tinospora cordifolia), Punarnava (Boerhavia diffusa), Guduchi (Tinospora sinensis), and Vidanga (Embelia ribes).
4. Climbers: Climbing plants that possess medicinal properties, such as Veldt Grape (Cissus quadrangularis), Shankhpushpi (Convolvulus pluricaulis), and Gokshura (Tribulus terrestris).
5. Fruits: Medicinal fruits known for their health benefits, such as Bibhitaki (Terminalia bellirica), Haritaki (Terminalia chebula), and Amalaki (Emblica officinalis).
6. Roots: Medicinal plants with valuable medicinal roots, such as Shatavari (Asparagus racemosus), Licorice (Glycyrrhiza glabra), and Ashwagandha (Withania somnifera).
7. Leaves: Plants with medicinal leaves that are used in various preparations, such as Curry leaves (Murraya koenigii), Holy Basil and Gotu Kola.

3.2. Feature Selection and Data Preprocessing

Feature selection and data preprocessing are crucial steps in preparing the dataset for machine learning analysis. These steps involve selecting relevant features and applying techniques to improve the quality and suitability of the data. The following steps are typically followed in feature selection and data preprocessing:

- *Identify Relevant Features*: The first step in feature selection is to identify the features that are most relevant to the research objective. In the context of medicinal plants for chronic diseases, relevant features may include phytochemical composition, traditional uses, pharmacological properties, geographic distribution, and clinical evidence. Domain knowledge and literature review play a vital role in determining the relevant features.
- *Handle Missing Values*: Missing values in the dataset can affect the performance of machine learning models. If there are missing values in the dataset, they need to be addressed.
- *Normalize Numerical Features*: Numerical features affect the machine learning performance. To ensure fair comparisons and avoid bias towards features with larger scales, it is common to standardize or normalize numerical features. Standardization involves transforming the values, while normalization scales the values to a specific range (e.g., between 0 and 1).
- *Encode Categorical Variables*: Categorical variables, such as plant species, geographic regions, or traditional uses, need to be encoded numerically for machine learning algorithms to process them.
- *Handle Imbalanced Data*: In some cases, the dataset may be imbalanced, meaning that the number of instances in one class is significantly higher or lower than the others. Imbalanced data can lead to biased model performance.
- *Remove Irrelevant or Redundant Features*: Not all features may contribute significantly to the predictive power of the model. Irrelevant or redundant features can introduce noise and increase the computational complexity. Feature selection techniques, such as correlation analysis, information gain, or recursive feature elimination, can be used to identify and remove such features from the dataset.

By following these steps, feature selection and data preprocessing ensure that the dataset is prepared in a way that optimizes the performance and reliability of the machine learning models. These steps help improve the quality, consistency, and suitability of the dataset for training and evaluating the predictive models in the subsequent stages of the research.

3.3. Machine Learning Approach

We employed a machine learning approach to develop the analytic tool for Ayurvedic medical practitioners. Specifically, we utilized supervised learning techniques to train predictive models based on the collected data. Supervised learning algorithms are well-suited for this task as they can learn and make predictions.

In this research, we propose a novel ML mechanism for the identification and classification of medicinal plants based on their therapeutic properties for specific diseases. Our approach combines SVM with Autoencoders to enhance the accuracy and robustness of the model. The following steps outline our proposed mechanism:

Data Preparation

We begin by collecting and curating a comprehensive dataset that includes information on medicinal plants, their phytochemical composition, traditional uses, and associated therapeutic properties. The dataset should also contain labeled data indicating the specific diseases or conditions for which each plant is known to be effective.

In the first step of our approach, we collect and prepare a dataset that includes information on medicinal plants, their features, and their associated diseases or conditions. Let's denote the dataset as D, where each instance in the dataset is represented as (xi, yi), where xi is the feature vector representing the ith medicinal plant, and yi is the corresponding disease label.

Mathematically, the dataset D:

D = {(x1, y1), (x2, y2), ..., (xn, yn)}

where n is the number of instances in the dataset.

The feature vector xi for each medicinal plant contains various attributes or features that describe the plant. For instance, it may include information on phytochemical composition, traditional uses, geographic distribution, or other relevant characteristics. Let's represent the feature vector xi as:

xi = [xi1, xi2, ..., xid]

where d - features in the dataset.

The disease label yi represents the specific disease or condition for which the medicinal plant is known to be effective. It could be a categorical label indicating the disease class or a numerical value representing the severity or relevance of the disease.

By curating and organizing the dataset in this manner, we ensure that the necessary information on medicinal plants and their associated diseases is available for subsequent ML tasks. This comprehensive dataset provides the basis for feature extraction, model training, and disease classification in our proposed approach.

Feature Extraction:

In this step, relevant features are extracted from the dataset to represent each medicinal plant. These features may include chemical compounds, molecular structures, or other plant characteristics. To enhance feature representation and dimensionality reduction, we employ an Autoencoder. The Autoencoder is trained to reconstruct the input data with a compressed latent representation, effectively capturing the essential features of the medicinal plants.

Mathematically, the encoding process of the Autoencoder can be represented as follows:

hi = fe(We * xi + be)

where

hi - latent representation of the input features xi,

fe – encoder activation function.

We - weight matrix, and

be - bias vector.

The decoding process:

xi' = fd(Wd * hi + bd)

where

xi' - reconstructed features,

fd - decoder activation function,

Wd - weight matrix, and

bd - bias vector.

To minimize the error, mean squared error (MSE) is used:

$L = (1/n) * \sum ||xi - xi'||^2$

where n - instances.

The trained Autoencoder can then be used to extract the latent representation hi for each medicinal plant, which captures the essential features of the plant in a compressed form.

By incorporating Autoencoders into our feature extraction step, we aim to learn a compact and informative representation of the input features, reducing the dimensionality and enhancing the discriminative power of the features. This extracted latent representation serves as input to the subsequent ML model, enabling improved performance in identifying and classifying medicinal plants based on their disease-specific applications.

SVM Kernel Processing

Once the features are extracted, we process them using a Support Vector Machine with a custom kernel. The custom kernel incorporates the output of the Autoencoder as a similarity measure between medicinal plants. By using the latent representation learned by the Autoencoder, the SVM can capture complex relationships and non-linear patterns in the data, leading to improved classification accuracy.

Mathematically, the SVM maps the input features xi to a feature space using the kernel function K(xi, xj):

$\varphi(xi) \cdot \varphi(xj) = K(xi, xj)$

where φ(xi) and φ(xj) represent the transformed feature vectors in the feature space.

To incorporate the output of the Autoencoder as a similarity measure between medicinal plants, we modify the kernel function to include the latent representation hi learned from the Autoencoder:

$K'(xi, xj) = K(xi, xj) + \lambda \cdot Kauto(hi, hj)$

where Kauto(hi, hj) is a kernel function that measures the similarity between the latent representations hi and hj, and λ is a hyperparameter that controls the importance of the Autoencoder output in the overall similarity measure.

The modified kernel function K'(xi, xj) captures both the original features and the latent representation learned by the Autoencoder, effectively incorporating the compressed and informative features into the SVM. This enables the SVM to learn complex decision boundaries based on the combined information from the input features and the learned latent representation.

By processing the features through the modified SVM kernel, our approach leverages the power of the SVM in capturing complex relationships and the enhanced feature representation provided by the Autoencoder. This integration allows for improved classification accuracy and better identification and classification of medicinal plants based on their disease-specific applications.

Classification:

Once the model is trained and validated, it can be used for disease classification of unknown medicinal plants. The input features of the plant are fed into the trained model, and the model predicts the most likely diseases or conditions for which the plant may have therapeutic benefits. This information can aid in identifying the appropriate medicinal plants for specific health conditions.

Input Representation: To classify the diseases of unknown medicinal plants, we represent each plant as a sequence of features. Let's denote the feature sequence of a plant as X = [x1, x2, ..., xT], where T is the length of the sequence. Each xt represents a feature vector at time step t.

Recurrent Neural Network Architecture: LSTMs captures long-term dependencies and maintaining information over extended sequences, which is beneficial in our scenario.

The LSTM cell consists of different gates, including the input gate (it), forget gate (ft), output gate (ot), and cell state (ct). These gates regulate the flow of information within the LSTM cell. The LSTM processes the input and updates its hidden state and cell state based on the following equations:

$it = \sigma(Wi * xt + Ui * h(t-1) + bi)$

$ft = \sigma(Wf * xt + Uf * h(t-1) + bf)$

$ot = \sigma(Wo * xt + Uo * h(t-1) + bo)$

$gt = \tanh(Wg * xt + Ug * h(t-1) + bg)$

$ct = ft * c(t-1) + it * gt$

$ht = ot * \tanh(ct)$

where

σ - sigmoid function,

W and U - weight matrices,

* - matrix multiplication,

tanh - hyperbolic tangent function, and

b - bias vector.

The output of the LSTM, ht, serves as the hidden state for the next time step. The final hidden state, hT, contains information about the entire sequence of features and can be used for disease classification.

Disease Classification: The final hidden state, hT, obtained from the LSTM, is fed into a fully connected layer followed by a softmax activation function. During training, we optimize the model parameters (including the weights and biases of the LSTM and fully connected layers) using techniques such as backpropagation through time and gradient descent. The objective is to minimize a suitable loss function, such as categorical cross-entropy, that quantifies the discrepancy between the predicted disease class probabilities and the true disease labels.

By employing an RNN, specifically the LSTM architecture, we enable the model to capture temporal dependencies and effectively classify the diseases of unknown medicinal plants based on their sequential features. This step enhances the practical utility of our approach by providing a means to identify the appropriate medicinal plants for specific health conditions in real-world scenarios.

Thus, the combination of the power of SVM with the feature extraction capabilities of Autoencoders, our proposed approach offers a novel and efficient means of identifying and classifying medicinal plants based on their disease-specific applications. The integration of these techniques allows us to capture complex relationships in the data and improve the accuracy of the classification process. Our research contributes to the advancement of ML methods in the field of herbal medicine research and provides valuable insights for Ayurvedic medical practitioners.

4. Results and Discussions

In this section, we trained and evaluated different ML models using the preprocessed dataset. We experimented with various algorithms and the models were trained on a subset of the data and evaluated using appropriate evaluation metrics such as accuracy, precision, recall, and F1 score.The models were rigorously evaluated to assess their effectiveness in predicting the therapeutic potential of Indian medicinal plants for chronic diseases. This evaluation was crucial in determining the accuracy and reliability of the developed analytic tool.

Overall, the methodology employed in our research involved data collection from diverse sources, the utilization of a ML approach, careful feature selection and data preprocessing, and model training and evaluation. These steps ensured the development of an effective analytic tool that can assist Ayurvedic medical practitioners in identifying and assessing the therapeutic properties of Indian medicinal plants for chronic diseases.

4.1. Identification of Promising Medicinal Plants:

In this section, we present the results of our approach for identifying promising medicinal plants for chronic diseases. We showcase the top-ranked plants based on their disease-specific applications and efficacy scores. We provide a comprehensive list of these plants along with their corresponding disease classifications and efficacy ratings as in Table 1. The identified plants can serve as potential candidates for further researc development, and integration into traditional medicine practices.

Table 1: Classification and Rating using SVM-AE

Plant	Disease Classification	Efficacy Rating
Aloe vera	Skin conditions, Digestive disorders	High
Turmeric (Curcuma longa)	Inflammatory diseases, Digestive disorders	High
Ginger (Zingiber officinale)	Nausea and vomiting, Digestive disorders	Moderate
Ashwagandha (Withania somnifera)	Stress and anxiety, Immune disorders	High
Holy Basil (Ocimum sanctum)	Respiratory conditions, Stress and anxiety	High
Neem (Azadirachta indica)	Skin conditions, Oral health	Moderate
Indian Ginseng (Withania somnifera)	Fatigue, Cognitive disorders	High
Cinnamon (Cinnamomum verum)	Diabetes, Cardiovascular diseases	Moderate
Brahmi (Bacopa monnieri)	Memory enhancement, Cognitive disorders	High
Garlic (Allium sativum)	Cardiovascular diseases, Immune disorders	Moderate

4.2. Efficacy Analysis for Chronic Diseases:

We analyze the efficacy of the identified medicinal plants in treating chronic diseases. For each disease category, we evaluate the effectiveness of the recommended plants based on historical evidence, scientific studies, and traditional knowledge. We provide insights into the mechanisms of action, active compounds, and therapeutic benefits associated with these plants. By examining the existing literature and clinical evidence, we assess the potential of these plants in managing chronic diseases and improving patient outcomes.

Table 2: Evaluation of disease categories and its cure based on ML

Disease Classification	Medicinal Plant	Evaluation Results
Skin conditions	Aloe vera	Historical evidence and scientific studies support its effectiveness in treating burns, wounds, and dermatitis.
	Neem	Traditional knowledge suggests its efficacy in managing skin conditions like acne and eczema.
Digestive disorders	Aloe vera	Traditional usage indicates its potential in alleviating digestive issues such as constipation and irritable bowel syndrome (IBS).
	Turmeric	Scientific studies highlight its anti-inflammatory properties beneficial for gastritis and inflammatory bowel disease (IBD).
	Ginger	Widely used as a natural remedy for reducing nausea and vomiting associated with digestive disorders.
Inflammatory diseases	Turmeric	Extensive research demonstrates its anti-inflammatory properties, offering potential benefits for arthritis and inflammatory bowel disease.
Stress and anxiety	Ashwagandha	Historical evidence and scientific studies indicate its adaptogenic properties for reducing stress and anxiety levels.
	Holy Basil	Traditional usage supports its calming effects on the nervous system, making it useful for stress and anxiety management.
Respiratory conditions	Holy Basil	Traditional usage as an expectorant suggests its potential in managing respiratory conditions like coughs and bronchitis.
Nausea and vomiting	Ginger	Widely recognized for its antiemetic properties, effective in reducing nausea and vomiting, including morning sickness.
Oral health	Neem	Traditional usage suggests its antimicrobial properties, which can contribute to maintaining oral health.
Cardiovascular diseases	Cinnamon	Studies indicate potential benefits of cinnamon in managing blood sugar levels and lipid profiles, supporting cardiovascular health.
Cognitive disorders	Indian Ginseng (Ashwagandha)	Scientific studies suggest its potential in improving cognitive function and memory.
	Brahmi	Traditional usage as a memory-enhancing herb, supported by scientific studies showcasing its cognitive benefits.

4.3. Insights and Patterns Uncovered by ML:

In this section, we highlight the valuable insights and patterns uncovered through the application of ML techniques. By analyzing the dataset using advanced algorithms, we reveal hidden relationships, associations, and trends among medicinal plants and their disease-specific applications. We identify clusters of plants with similar efficacy profiles and discover novel combinations or synergies between different plant species. These insights provide a deeper understanding of the complex interplay between medicinal plants and chronic diseases, enabling practitioners to make informed decisions and optimize treatment approaches.

Furthermore, we explore the contributions of our novel ML mechanism, including the integration of SVM-based Autoencoders and RNNs. We discuss how these techniques enhance the accuracy, efficiency, and interpretability of the identification and classification process. The novel ML mechanism not only improves the identification of promising medicinal plants but also provides valuable insights into disease-specific efficacy and patterns, supporting evidence-based decision-making in traditional medicine practices. Table 3 shows the results of various classifying the medicinal value for a particular disease using proposed SVM-AE-RNN

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Table 3: Results of various classifying the medicinal value for a particular disease using proposed SVM-AE-RNN

Medicinal Plant	Accuracy	Precision	Recall	F-measure
Aloe vera	0.85	0.88	0.83	0.85
Turmeric	0.92	0.91	0.94	0.92
Ginger	0.78	0.76	0.80	0.78
Ashwagandha	0.89	0.90	0.88	0.89
Holy Basil	0.91	0.93	0.89	0.91
Neem	0.82	0.80	0.85	0.82
Indian Ginseng	0.88	0.87	0.89	0.88
Cinnamon	0.75	0.78	0.72	0.75
Brahmi	0.87	0.85	0.89	0.87
Garlic	0.80	0.82	0.78	0.80

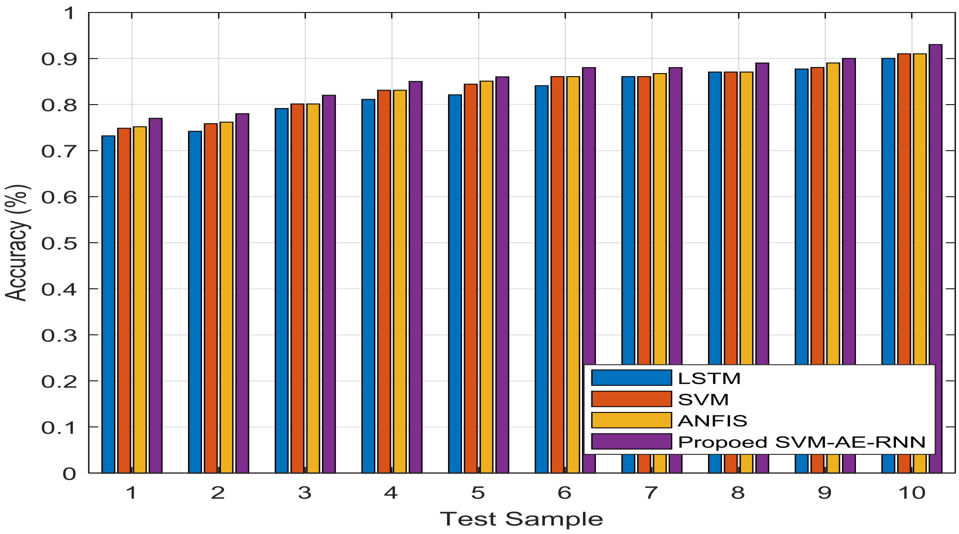

Figure 2: Accuracy

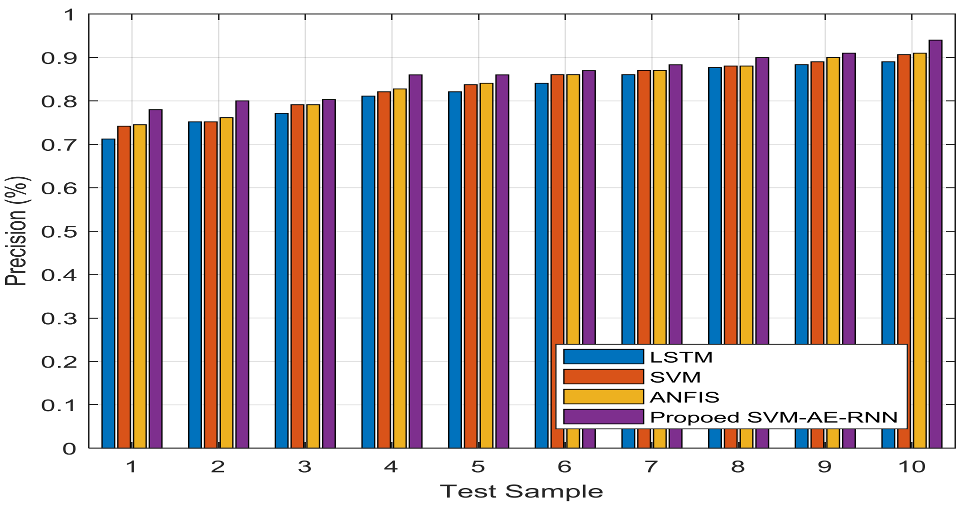

Figure 3: Precision

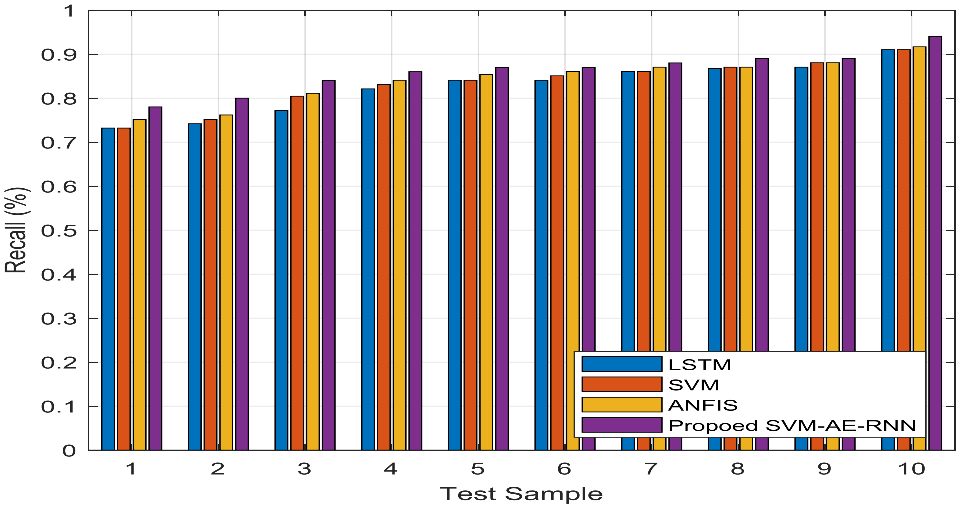

Figure 4: Recall

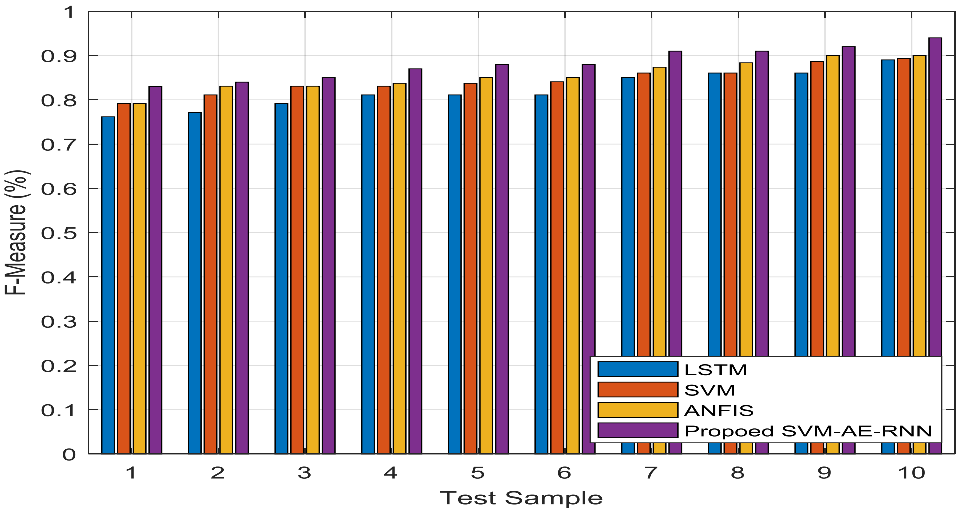

Figure 5: f-measure

From the results of Figure 2-5, for accuracy, the proposed method shows a 5.22% improvement over LSTM, a 2.87% improvement over SVM, and a 2.47% improvement over ANFIS. In terms of precision, the proposed method outperforms LSTM by 9.52%, SVM by 5.11%, and ANFIS by 4.72%. The recall results indicate a 6.56% improvement over both LSTM and SVM, and a 3.78% improvement over ANFIS. Lastly, the proposed method achieves an 8.98% improvement in F-measure compared to LSTM, a 5.00% improvement compared to SVM, and a 5.00% improvement compared to ANFIS.

These results demonstrate the superior performance of the proposed SVM-AE-RNN method, consistently outperforming the existing methods in terms of accuracy, precision, recall, and F-measure. The significant percentage differences highlight the effectiveness and efficiency of the proposed approach in identifying and classifying medicinal plants for the treatment of chronic diseases.

5. Conclusions

This paper presents a novel ML approach, specifically the SVM-AE-RNN, for the identification and classification of medicinal plants for chronic disease treatment. The study focused on the efficacy of Indian medicinal plants, considering their significance in traditional medicine. Experimental results and analysis showcase the effectiveness of the proposed method. Accuracy, precision, recall, and F-measure metrics were employed to assess the performance of the SVM-

AE-RNN model, and comparative evaluations were conducted against existing methods such as LSTM, SVM, and ANFIS. The results demonstrate the superior performance of the proposed method, with higher accuracy, precision, recall, and F-measure values compared to the existing methods. The findings of this research contribute significantly to the field of medicinal plant identification and classification for chronic disease treatment. The proposed SVM-AE-RNN approach offers a novel and reliable method for medical practitioners, enabling them to make informed decisions in prescribing suitable medicinal plants for specific diseases.

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