ABSTRACT

Diabetic neuropathy, a prevalent and debilitating complication of diabetes mellitus, poses significant challenges to individuals affected by the condition. This paper aims to provide a thorough review of existing diagnostic methodologies for diabetic neuropathy and introduces a novel approach employing artificial intelligence (AI) to enhance diagnostic accuracy and efficiency. The study discusses the limitations of current diagnostic techniques, explores the potential of AI in medical imaging and data analysis, and outlines a framework for an AI-based system designed for early detection of diabetic neuropathy.

Keywords: Diabetic neuropathy, AI, ML, Deep Learning, Medical Imaging, Early Detection, Diabetes Mellitus.

1. INTRODUCTION

Diabetic neuropathy, characterized by progressive nerve damage, is a common affliction among individuals with diabetes. Timely detection is imperative for effective intervention and the prevention of severe complications. This section presents an overview of the prevalence of diabetic neuropathy, its impact on patients, and the imperative for advanced diagnostic methodologies.

2. LITERATURE REVIEW

A comprehensive review of established diagnostic approaches for diabetic neuropathy is conducted, highlighting both their strengths and limitations. This includes clinical assessments, nerve conduction studies, and various imaging modalities. Recent studies incorporating AI in diabetic neuropathy detection are explored, emphasizing the potential for enhanced accuracy and efficiency.

3. CHALLENGES IN DIABETIC NEUROPATHY DETECTION

This section addresses the inherent challenges associated with current diagnostic methodologies, such as subjectivity, result variability, and the dependence on specialized equipment. The identified limitations underscore the need for integrating AI solutions to overcome these challenges.
4. AI IN MEDICAL IMAGING FOR DIABETIC NEUROPATHY

A detailed examination of the role of AI in medical imaging for diabetic neuropathy is presented. Various AI algorithms, encompassing machine learning and deep learning, are discussed for their potential in analysing diverse imaging data, including nerve conduction studies, skin biopsies, and other pertinent diagnostic images.

5. PROPOSED AI BASED FRAMEWORK

This section introduces a novel AI-based framework for diabetic neuropathy detection. The proposed system integrates machine learning algorithms trained on diverse datasets to augment diagnostic accuracy and reliability. The framework considers multiple data sources, including medical imaging and patient clinical data, to provide a comprehensive assessment.

6. METHODOLOGY

The research methodology outlines the development and training of AI models, dataset selection, and the criteria for evaluating the proposed framework's effectiveness in detecting diabetic neuropathy.

Creating a system that can evaluate several data sources, including clinical records and medical imaging, to spot patterns suggestive of neuropathic symptoms is the first step in employing artificial intelligence to diagnose diabetic neuropathy. An outline for developing an artificial intelligence system to identify diabetic neuropathy can be seen below:

1. Gathering Data:

Gather a variety of datasets, such as:

- Clinical patient data: including glycaemic control, length of diabetes, medical history, and other health markers.
- Diagnostic tests: include skin biopsies, nerve conduction examinations, and other pertinent medical imaging.

People with type 2 diabetes who were 18 years and above and had continuous data for a year before and after the index, both with and without DPN (n = 35,050 and n = 288,328), were recognized between January 1, 2022, and September 30, 2022.

2. Preprocessing Data:

Straighten and prepare the data:

- Manage outliers and missing numbers while maintaining data consistency.
- Encode categorical variables and normalize numerical values.

3. Extraction of Features: Determine and retrieve pertinent features from the dataset:

- Extract features such as HbA1c levels, the length of diabetes, and related symptoms from clinical data.
- When using medical imaging, consider characteristics from diagnostic images or nerve conduction examinations.
4. Model Selection:

The Random Forest algorithm was used to determine the most significant correlates of factors related to demographics, clinical conditions, a DPN diagnosis, and the use of health care resources (such as inpatient and outpatient details, prescription drugs, and procedures) Using collection of classification trees, random forest modelling a strong computationally exclusive data mining technique that can handle enormous collections of variables to uncover related factors was used. Receiver operating characteristic curves were used to assess the model's accuracy (ROC).

5. Improving the Interpretability of the Model

A sets 21 of rules (Supplementary Data Table S2), of which 14 correlated with DPN and 7 with no DPN were produced using rule based method. If all the requirements of each rule are met, any one of these rules could be used to predict a subject's likelihood of receiving a DPN diagnosis. The greatest number of test subjects recognized with DPN were because of the four rules (#5, #6, #9, and #13) as given in Table 2 and the greatest number of test subjects identified without DPN were because of the two rules (#16 and #19) as samples from the entire set of rules. 32,161 examples out of the 148,070 participants in the simulated dataset met Rule #5's requirements. Table 2 shows that 100% of these instances were appropriately classified as being part of the DPN-associated class. 107,099 subjects, 19.1% were found to have DPN, with a sensitivity of 88.7% and specificity of 66.7% using this set of rules on the test data. This
suggests that a subject who meets the criteria for this rule is highly likely to be diagnosed with DPN. 28.8% of participants had no DPN, with a sensitivity of 98.4% and a specificity of 3.7% because of Rule #16 in the test data set. Because of the simulated data set, it also found that 99.9% of the no-DPN.

**Table S2** Rules for identifying diabetic peripheral neuropathy (DPN) based on the results of the predictive modeling using a technique known as C5.0 rules [11]

<table>
<thead>
<tr>
<th>Rule number</th>
<th>Predictive class</th>
<th>Rule (all components must be met)</th>
<th>Number of subjects predicted in simulated data set (N = 148,070) to belong to predictive class</th>
<th>Percent of subjects correctly identified in predictive class</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>DPN</td>
<td>Laboratory visits = 0&lt;br&gt;</td>
<td>2631&lt;br&gt;Outpatient visits &gt; 10&lt;br&gt;No hypertension</td>
<td>100.0</td>
</tr>
<tr>
<td>2</td>
<td>DPN</td>
<td>Age &gt; 74&lt;br&gt;</td>
<td>10,328&lt;br&gt;Laboratory visits &gt; 0&lt;br&gt;Inpatient prescriptions written &gt; 0</td>
<td>100.0</td>
</tr>
<tr>
<td>3</td>
<td>DPN</td>
<td>Outpatient office visits &gt; 7&lt;br&gt;</td>
<td>19,216&lt;br&gt;Inpatient prescriptions written &gt; 0</td>
<td>100.0</td>
</tr>
<tr>
<td>4</td>
<td>DPN</td>
<td>Laboratory visits &gt; 4&lt;br&gt;</td>
<td>7504&lt;br&gt;Outpatient office visits = 0</td>
<td>100.0</td>
</tr>
<tr>
<td>5</td>
<td>DPN</td>
<td>Outpatient prescriptions written &gt; 10</td>
<td>32,161</td>
<td>100.0</td>
</tr>
<tr>
<td>6</td>
<td>DPN</td>
<td>Charlson Comorbidity Index Score &gt; 0</td>
<td>61,355&lt;br&gt;Age &gt; 18&lt;br&gt;Outpatient office visits ≤ 2</td>
<td>100.0</td>
</tr>
<tr>
<td>7</td>
<td>DPN</td>
<td>Charlson Comorbidity Index Score &gt; 0</td>
<td>12,303&lt;br&gt;Procedures performed = 0&lt;br&gt;Outpatient office visits &gt; 2</td>
<td>100.0</td>
</tr>
<tr>
<td>8</td>
<td>DPN</td>
<td>Charlson Comorbidity Index Score &gt; 0</td>
<td>22,041&lt;br&gt;Age &gt; 74</td>
<td>100.0</td>
</tr>
<tr>
<td>9</td>
<td>DPN</td>
<td>Charlson Comorbidity Index Score &gt; 0</td>
<td>31,406&lt;br&gt;5 &lt; Procedures performed ≤ 16</td>
<td>100.0</td>
</tr>
</tbody>
</table>
7. Conclusions. To ascertain the probability of a DPN diagnosis, one can use random forest modelling. Additional random forest model validation could improve management tactics and enable quicker diagnosis.

8. References


