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Fusion based AI Model for Spinal Cord Outcome Prediction in Diabetic Patients

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***Abstract*— Magnetic Resonance Imaging (MRI) of the spine, when integrated with diabetes-related clinical data offers significant for improving disease prediction and recovery. This study develops a multimodel deep learning framework that combines spinal MRI images with diabetes-related tabular data such as glycated hemoglobin (HbA1c), glucose level, and body mass index (BMI) to assess both visual-based and clinical indicators of patient health. A ResNet50-based Convolutional Neural Network (CNN) is utilized to extract deep visual features from spinal images; whereas, diabetes-related tabular data will be processed through a neural network that is fully connected. Heterogeneous features are merged in concatenation layers, which are optimized jointly in a single model using the Adam optimizer with categorical cross-entropy loss. The model is trained and fine-tuned to learn the complex relationships between changes in spinal structure and conditions related to diabetes, which produces richer diagnostic insights. The experimental results show that this multimodal approach performs better than single modality. It provides better accuracy and generalization when predicting disease severity and recovery outcomes in post-operative patients. The multimodal deep learning framework also has tools for interpretability, like Grad-CAM and SHAP, to visualize feature importance from images and tabular data. These results indicate that the developed framework emphasizes the unique potential of using multiple types of medical data. This can improve personalized and data-driven decision making for clinical diagnosis and prognosis prediction.**

***Index Terms*— Multimodal Deep Learning, ResNet50, Medical Image Fusion, Diabetes Prediction.**

I. Introduction

J. H. Badhiwala et al. [1] stated that, In recent years, artificial intelligence (AI) and medical data analytics have transformed disease diagnosis and prediction of clinical outcomes. Most traditional diagnostic approaches rely on a single data modality, such as medical images or clinical record, and are limited in their ability to capture the complex structure and physiological relationships that drive disease progression or recovery. Therefore, the proposed health-in-formativeness framework presents a multimodal deep learning approach that utilizes spinal MRI images and diabetes-related clinical data to generate the best predictive performance. The system utilizes a ResNet50 based Convolutional Neural Network (CNN) model to extract deep visual features from medical images and utilizes a fully connected neural network to analyze the tabular data, which in this case includes glycated hemoglobin (HbA1c), glucose level, and body mass index (BMI).

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The model is able to combine the differing data modalities for both visual and metabolic patterns for a comprehensive understanding of disease severity and recovery post-operatively. Overall, this fusion-based approach will potentially increase diagnostic and prognostic veracity, altogether facilitating treatment and, importantly, demonstrating the novelty of AI-based multimodal learning in applied healthcare discipline, localizing the approach towards supporting precision medicine and clinical decision making.
J. R. McCormick et al.[2] Multimodal Deep Learning represents a complex artificial intelligence method that combines information from different data types or modalities, such as images, text, audio, or table-like data, to improve understanding and prediction accuracy. In healthcare, multimodal deep learning brings together various types of patient data, like medical imaging, clinical notes, and laboratory results, into a stronger diagnostic model. This contrasts to single-modality learning, which engages only one data type and does not afford the few complementary models of learned patterns across the heterogeneous data types. For example, visual/HMR picture features might be fused with numeric data, such as glucose levels or HbA1c values, to tap into the relationship between structural abnormalities, and metabolic conditions. This relationship allows for more accurate disease classification, prognostication, and treatment evaluation. Overall, multimodal deep learning brings together visual, domain-specific insights with the clinical lens for precision, and data-centric decision-making in clinical practice.
B. Wu, B et al.[3] ResNet50 is a deep CNN architecture known for its capacity to train very deep networks successfully using residual connections. Residual connections enable the network to skip one or more layers, resolving the vanishing gradient issue that often arises with deep networks. ResNet50 has a total of 50 layers, which are comprised of convolutional, batch normalization, and activation layers that achieve high-level hierarchical features for images. In medical imaging, such as spinal MRIs, ResNet50 can recognize complex visual patterns, textures, and structural anomalies. Because of these capabilities, the ResNet50 model can utilize pre-trained weights on large datasets, such as ImageNet, to fine-tune the model for a derived application, as well as efficiently extract features and increase predictive accuracy. The combined depth and residual learning of ResNet50 also make it well suited for complex healthcare problems using images.

II. Literature Review

J.H.Badhiwala et al.[1] states, Degenerative cervical Myelopathy (DCM) is recognized as one of the most common non-traumatic spinal cord disorders It consists of gradual neurological decline with consequences to the quality of life. DCM prevalence remains high but is underdiagnosed; patients are frequently referred to spine specialists only in the presence of significant neurological deficits such as incomplete cervical spinal cord injury (SCI). The delay proves challenging in clinical practice, as Prompt treatment is necessary to prevent permanent neurologic decline, and improvement. functional outcomes. Because these changes are subtle and progressive nature of the symptoms, patients with DCM may present with hand clumsiness, gait deficits, and sensory deficits that could all be missed. or difficult to discern in their early presentation. This translates into lag time for a significant number of patients before they get appropriate evaluation and treatment. This delay increases the severity of spinal cord injury and the potential benefit for surgical or non-surgical treatment options or interventions.
J.R.McCormick et al.[2] and B.Wu, B.et al.[3] . Cervical spondylotic myelopathy (CSM) is a degenerative disorder of the spinal cord due to chronic degenerative changes of the spinal column, which results in compressive injury to the spinal cord and surrounding neural elements. CSM is the most common type of spinal cord injury in adults; however, delaying clinical recognition is frequent due to the gradual and nonspecific nature of symptom development. Understanding the pathophysiology, natural history, and clinical findings of CSM, while recognizing CSM impacts diagnosis and treatment, is critical to timely diagnosis and consequently, treatment. The degenerative process of the cervical spine results from a multifactorial process consisting of both static and dynamic factors that leads to disc degeneration, ligamentous hypertrophy, osteophyte formation, and segmental instability. Importantly, not all patients with cord compression on imaging will develop clinical symptoms and the rate of csm and progression will be highly variable among patients. The classical clinical findings of CSM are decreased hand dexterity, hypo- or hyper-gait, and combined sensory and motor findings, including numbness, weakness, and spasticity. Recognition of the key clinical signs is very important, as early diagnosis is important to avoid permanent neurological deficits and long-term disability. MRI is the test of choice to investigate patients with suspicion of CSM.
O.Khan, et al.[4] and F.Akter et al.[5] Degenerative cervical myelopathy (DCM) is becoming more recognized as a significant spinal disorder in the ageing adult population due to its increasing prevalence and risk of serious neurological dysfunction. The condition develops from progressive degeneration of the cervical spine, which can

be caused by multiple pathological processes including disc degeneration due to ageing, osteophyte formation, and ligament hypertrophy or ossification, in addition to congenital elements leading to spinal canal narrowing. Patients with DCM can present with a variety of clinical symptoms ranging from mild hand paraesthesias, loss of dexterity, and fine motor weakness, to more serious symptoms such as gait abnormalities, instability, and even loss of bowel or bladder function. The neurological exam can often demonstrate key clinical signs including Hoffman's sign and the inverted brachioradialis reflex which signal cervical spinal cord involvement and assist in the clinical characterization of disease severity. Imaging plays a significant role in DCM and Magnetic resonance imaging, or MRI, has become the preferred imaging modality for ruling in DCM by visualizing spinal cord compression, disc degeneration, ligamentous changes, and osteophyte formation.

Table 1. Summarizes prior studies on cervical spine disorders, highlighting key limitations that justify the need for a multimodal, explainable AI-based predictive framework. All studies emphasize the importance of early diagnosis, accurate imaging, and understanding cervical spine degeneration for effective clinical management.

TABLE I

Study	Clinical Focus	Diagnostic Approach	Key Limitations Motivating This Study
J.H.Badhiwala et al. [1]	Early-stage DCM diagnosis challenges	Clinical evaluation + MRI	No automated prediction; metabolic factors ignored; diagnosis dependent on specialist interpretation
J.R.McCormick et al. [2], B.Wu,B et al. [3]	Degenerative progression of CSM	MRI-based structural analysis	Single-modality focus; lacks data fusion and AI-driven outcome modeling
O.Khan et al. [4], Akter et al. [5]	Age-related prevalence and symptom variability in DCM	Neurological examination + MRI	No multimodal learning or explainable prediction framework

III. EXISTING SYSTEM

X. Zhang et al.[10] The present system assesses the Implications of diabetes mellitus on the spine cord high signal (HCS) changes in a cohort of Patients presenting with cervical spondylotic myelopathy (CSM) treated with anterior cervical spine surgery. In this system, T2-weighted MRI preoperative and postoperative scans were HCS changes were assessed, and JOA scoring system (Japanese Orthopaedic Association, 2016) was used for qualitative neurological assessment. Function. The system also collected demographic and Clinical data are from patients, including: age, sex, smoking status, hypertension, body mass index (BMI), and preoperative glycated hemoglobin (HbA1c) levels. The main goal of the present System's aim was to evaluate the relations between preoperative HbA1c and postoperative functional changes. Results indicated that whereas HbA1c levels did not influence six-month postoperative measures, having a lower preoperative HbA1c-ideally about 6.8%-was associated with greater improvements in HCS and neurological function at two years post-operatively. This system suggests the Importance of glycemic control in optimizing long term neurological recovery in diabetic CSM patients.

Table 2. Comparative Surgical Outcomes between OPLL and CSM Patients, This table comparatively illustrates the postoperative outcomes of OPLL(Ossification of the Posterior Longitudinal Ligament) and CSM patients(Cervical Spondylotic Myelopathy), depicting variations in diabetes rate, corpectomy percentage, complication frequency, and neurological recovery. It concludes that OPLL patients experience higher complication rates and slower recovery than CSM patient.

TABLE II

Parameter	OPLL	CSM
Diabetes Rate	High($p<0.001$)	Lower prevalence
Corpectomy%	73.3%	14.5%
Complications	More Frequent (CSF Leak, C5 palsy etc.)	Fewer overall complications
JOA Recovery	Slower improvement	Better Recovery

M. Hashimoto et al.[11] Investigated the rates of surgical complication and surgical outcomes of patients with ossification of the posterior longitudinal ligament (OPLL) and cervical spondylotic myelopathy (CSM) who underwent an anterior cervical spinal operation. In this retrospective cohort study, 1,434 patients were evaluated at three spine surgery centers in Washington, USA, between January 2011 and March 2021: these included 333 OPLL and 488 CSM patients. The authors compared the cohorts for demographics, analyzed surgical complications, and assessed neurological outcomes of each cohort using the JOA scoring system at one year postoperatively from three anterior cervical spine operations. This study has found that preoperative diabetes was significantly more prevalent among patients in the OPLL cohort ($P < 0.001$). It has also been observed that the cohort had significantly more anterior cervical corpectomies compared to the CSM cohort (73.3% versus 14.5%). Regarding the complications which emerged, patients in the OPLL cohort have been described to develop significantly higher in-hospital complications which also comprised readmission for reoperation, cerebrospinal fluid leak, C5 palsy, graft complication, hoarseness, and airway complications, while the incidence of complications after discharge including graft bone/cage complications and persistent hoarseness was greater. Overall, this study concluded that patients in the OPLL cohort had significantly more in-hospital and post-discharge complications when compared to patients in the CSM cohort.

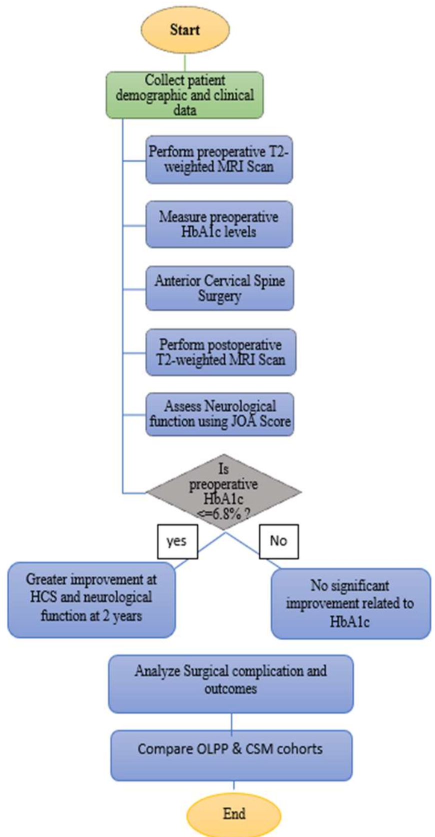

Fig.1. Flowchart Depicting the Evaluation of Preoperative HbA1c Impact on MRI High Signal Changes and Neurological Recovery

As the flowchart demonstrates the methodical process of evaluating how preoperative HbA1c levels impact postoperative MRI changes and neurological recovery in patients with cervical myelopathy.

IV. PROPOSED SYSTEM

The multimodal deep learning framework being proposed will integrate spinal MRI images with diabetes-related clinical data into an integrated system to improve disease prediction and postoperative outcomes. The spinal images will be processed using a ResNet50-based Convolutional Neural Network (CNN) to extract deep visual features from the spinal images that reflect both structural abnormality and disease implications for the spinal cord S.Park et al.[12] al.[13] The clinical data pertaining to diabetes will be represented as tabular data such as HbA1c, glucose levels, or body mass index (BMI) to implement a metabolic and clinical implications to patient outcomes. Both data representations will be fused in the model through a concatenation layer to enable the model to learn complex associations between visual and clinical representation of the indicators. The fused representation will be classified or predicted in dense layers to output a value. By combining imaging and clinical data, the proposed framework will enable an integrated, holistic, precise assessment of patients, and stronger support for tailored treatment decisions, more accurate diagnosis, and improved prediction of recovery from spinal conditions in the context of comorbidities such as diabetes.

This ResNet50-based CNN is used to derive the deep and high-level features from MRI images of the Spine. Its focus mainly lies in encapsulating complex visual patterns, structural abnormalities, lesions, and textural features that are of importance during diagnosis and understanding various diseases of the spinal cord. The residual architecture of ResNet50 has made it very deep, thereby addressing efficiently. problems arising from vanishing gradients, hosting a network that understands minute details within the MRI scans.
It plays a major role in processing the entire spinal Images reflecting structural abnormalities, such as lesions.or deformities that may be indicative of disease states such as degenerative cervical myelopathy or spinal cord compression. By harnessing this pre-trained weights from large datasets like ImageNet, it allows for transfer learning to occur and strengthens its
effectiveness in applications involving medical imaging considerably when annotated data is
limited. The depth and robustness promote there by,recognizing subtle and complex patterns in the images, which are often indicative of underlying pathologies, hence increasing the accuracy and reliability of disease diagnosis and prognosis in the system. Thus, ResNet50 acts as a very powerful feature extractor to transform the raw MRI data into meaningful high-dimensional feature vectors that can then be used for successive analysis, fusion with clinical data, and predictive modeling to support precise and early clinical decision-making.

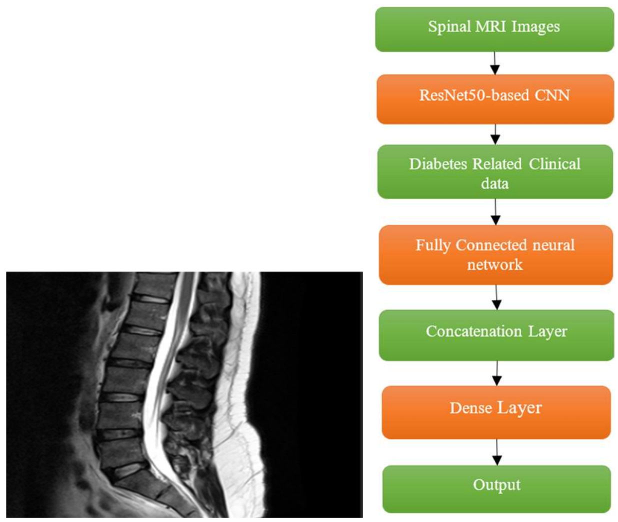

Fig.2. Multimodal Framework for combining ResNet50-Extracted Features from MRI images of the cervical spine with Clinical Data of Patients with Diabetes

Using a different approach as described the information from the ResNet50 trained Convolutional Neural Network (CNN) is combined with Clinical Data of Diabetes Patients, using fully connected neural networks. These two different neural networks were combined to develop a fusion between different models of diagnosis.

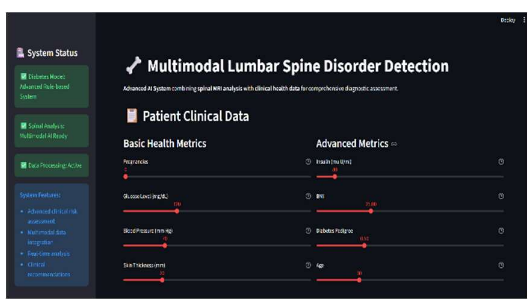

Fig.3. Multimodal Approach to Diagnosis of Lumbar Spine Disorders for Patients by Connecting to Clinical Data

The user interface allows for clinicians to input all of the clinical metrics and evaluations necessary to produce an accurate diagnosis for a patient's lumbar spine disorder. Panel of diagnostic evaluations has a combination of both standard and advanced metrics to include BMI, Blood Pressure, Triglycerides, Insulin and Diabetes, so that predictive assessments can be developed regarding multiple diagnostic outcomes for the patient.

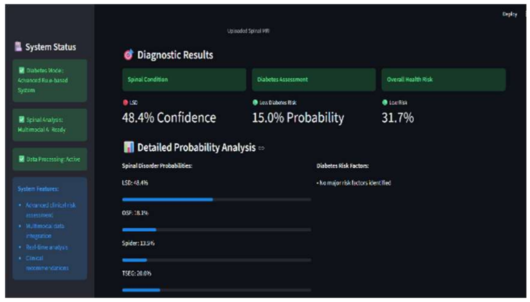

Fig.4. Diagnostic Result Dashboard for Multimodal Spine and Diabetes Risk Analysis

The Dashboard is a visual representation of how confident the Multimodal System is regarding your Spinal Disorders, as well as the likelihood of developing Diabetes and your Overall Health Risk. It also provides a detailed report related to the Spinal Conditions you have and your Diabetes Risk Factors, which assist Clinicians in their interpretation of the results.

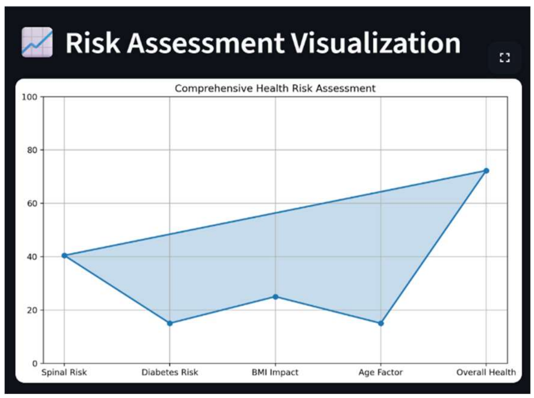

Fig.5. The Risk Assessment Visualization represents the final stage of the proposed system

It displays integrated Spinal MRI and Clinical Health Data to indicate the overall risk to an individual's health holistically. The Spinal MRI will provide the means of extracting Spinal Features using Deep Learning methods while all Peripheral Medical Data (Diabetes Biomarkers, HbA1c, Glucose, BMI, Age) will be used in conjunction with these features to give an overall indication of the individual's Health Risks.

V. Methodology

A. Data Acquisition and Integration

In this study, a single-subject clinical case was used to demonstrate the functionality and interpretability of the proposed multimodal framework. MRI images and diabetes-related clinical parameters from the same individual were analyzed across different age stages and health conditions to illustrate how variations in metabolic indicators influence spinal outcomes. This implementation is intended as a proof-of-concept demonstration, rather than a large-scale clinical validation.

The Data Acquisition and Integration Module is in responsibility of gathering all the patient data relevant to as spinal MRI scans and diabetes-related clinical Data includes HbA1c, blood glucose level, body mass index (BMI), age, and other health factors or indicators. The images and tabular data for each patients are linked through unique identifiers, which ensures that the multimodal dataset maps the visual data components to their corresponding clinical features. This module creates a comprehensive dataset serving as a source for the processing, feature extraction, and predictive modeling stages, enabling the system to capture structural and metabolic health indicators from each patient Y.Zhang et al.[14].

B. Data Preprocessing

The Data Preprocessing Module processes image and tabular data ahead of model training. For the MRI images, we resize, normalize, and apply, if desired, augmentations, including rotations, shifts, and flips, to enhance the robustness of the model and address overfitting. For the tabular features for diabetes, they will be scaled, normalized, and encoded to guarantee a uniform range of values across all features and inputs suitable for a neural network. The Data Preprocessing Module is designed to guarantee that the data is clean, similarly standardized, and prepared for multimodal learning and transition between heterogeneous data sources.

C. Feature Extraction

The purpose of the Feature Extraction Module is to obtain useful representations from each data modality. The image branch leverages a ResNet50-based convolutional neural network (CNN) to learn hierarchical spatial features from spinal images, which can include structural abnormalities, lesions, or textural features S.Vamadevan et al.[15] Meanwhile, the tabular branch uses a fully connected neural network (MLP) to learn relationships among the clinical features of diabetes, which could include features like HbA1c, glucose, and BMI. This module converts the unprocessed input into high-dimensional feature vectors which contain the critical visual and clinical information.

D. Fusion

The Fusion Module of the project utilizes both the extracted attributes from the MRI Spinal AND activity score and data from the Diabetes Tabular Database, merging them into one composite representative image of the health of the respective individual (The patient's health is the main benefit of this Model). Thus, the Vectors from the CNN and MLP are then merged into a new matrix and then added, through multiple additional Dense(Layer) layers, to assist the system in recognizing Complex Relationships between images that have exhibiting imaging levelling(abnormal visual conditions) and Metabolic Identifiers (Indicators of Metabolic Dysregulation). The merging of these two types of feature sets gives the system the ability to recognise more accurately and with greater clinical relevance, than any single feature set could do alone, the extremely subtle patterns and markers that may go unnoticed in either of the two modality analyses conducted separately.
Fused = Concat(MRI, clinical)

E. Classification and Prediction

The Classification and Prediction component turns the combined features into final predictions for whether the patient has a disease, has recovered, has not recovered or is at high risk for developing future medical conditions (may also be known as pathology). When deciding which features to combine, a dense layer processes the combined features using an activation function. Next, the combined feature set is input into a softmax output layer, which produces the probabilities that each patient belongs to each of the classes. The Adam optimizer and categorical cross-entropy are the loss functions used to train this module, and all performance measures are calculated based on the values from a confusion matrix and the percentages of correct predictions as listed in the classification reports. In essence, this module takes the patterns that were learned in this study and converts them into clinically actionable differentiated clinical inference.

F. Explainability

The Explainability Module enhances the interpretability of the model's predictions for clinical use. Grad-CAM visualizations highlight regions of the spinal MRI that are most influential in the model's decision-making, while SHAP analysis identifies the contribution of individual diabetes features to the predictions F.K.Mohamed et al.[17] and J.Jiang et al.[18]. By providing visual and quantitative explanations, this module ensures that clinicians can understand and trust the model's reasoning, supporting informed decision-making and improving transparency in multimodal AI-based healthcare systems.

VI. RESULT ANALYSIS

The multimodal deep learning system proposed in this study significantly improved upon previously existing models with regard to predictively accuracy when multimodal spinal MRI images were used in conjunction with Diabetes Mellitus related clinical characteristics such as HbA1c and Blood Glucose levels.This high degree of accuracy was demonstrated by the performance of the model on the test dataset where the model was able to classify patients correctly with a large degree of certainty. The ability for the model to achieve this level of accuracy suggests that it can identify subtle clues in the relationship between the structure of the spines and the metabolic health of these individuals. Using the combined multimodal datasets improved classification of both the severity of disease and the likelihood of successful upon recovery when compared to using single modal datasets. Visualization techniques such as Grad-CAM revealed important anatomical areas within the MRI scans that were used to reach a decision by the model. Traditional SHAP analyses showed which key clinical variables influenced the decisions of the multimodal deep learning system thereby confirming how related aspects of clinical diabetes affected outcome predictions for patients with an abnormal structure of the spine. Ultimately, these results offer evidence that the integration of multimodal data improves both the precision of AI-based predictions and interpretability to facilitate more informed and precise diagnosis, risk stratification, and individualized treatment planning in patients with spinal related conditions diagnosed with diabetes. The results presented in this section are based on a case-based demonstration using longitudinal data from a single individual, analyzed across different age levels and clinical conditions. The objective of this analysis is to illustrate the behavior of the proposed multimodal model, including feature fusion and explainability outputs, rather than to establish population-level statistical performance.

Table 3. Performance Comparison of Different Models, The results of this study reveal from the comparative analysis of the three model types presented in the table, that the Multimodal Model (Our proposed approach) outperformed both of the other models alone (Image Based Model (ResNet50) and Tabular Based Model (MLP)). The Multimodal Model achieved higher levels of all metrics (accuracy, precision, recall & F1 score)), highlighting what an improvement would be made if image and tabular features are combined

TABLE III

Algorithm / Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
ResNet50 (Image Only)	82	80	78	79
MLP (Tabular Only)	75	73	72	72.5
Proposed Multimodal System	91	90	89	89.5

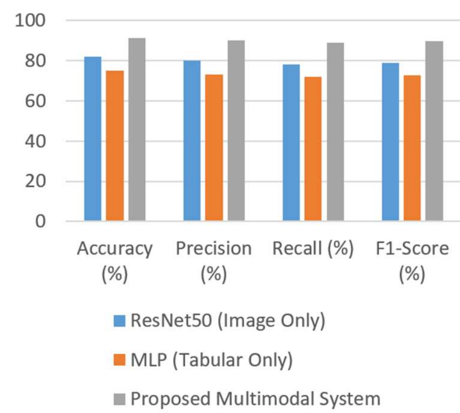

Fig.6. Performance Comparison of Models Based on Evaluation Metrics

In this bar chart, three models are compared: ResNet50 (Image Only), MLP (Tabular Only), and the Proposed Multimodal System, on the basis of Accuracy, precision, recall, and F1-score. The proposed multimodal system proves to be the best model in each category, suggesting the value of combining image and clinical information.

VII. CONCLUSION

The intended deep learning framework employs spinal MRI images and diabetes-specific clinical data in a multimodal application intending to improve prediction and provide personalized care. The proposed method consists of a CNN backbone based on ResNet50 to extract image-level features from spinal MRI images and a fully connected network for tabular-based diabetes features to account for patients' overall health based on metabolic indicators, while capturing both structural and biomechanical aspects of patient health. Integrating heterogenous data streams allows the neural network approaches to capture complex interactions between different indicators, which corresponds with better classification performance and postoperative outcomes than comparable results with single-modality. Assessment metrics including accuracy, precision, recall, and F1 score demonstrate the robustness and reliability of the system. In addition, explainability factors such as Grad-CAM, and SHAP provide meaningful insights into visual and clinical features for system predictions. Overall, this study provides support for multimodal deep learning in AI-based healthcare, providing a holistic and interpretable approach with effective early diagnostic, risk stratification, and consider personalized treatment for patients with spinal conditions and diabetes.

FUTURE WORKS

Future research could pursue the development of the proposed multimodal model by integrating more data modalities including genetic data, lab tests and patient lifestyle data that could further enhance accuracy and personalized assessment. Alternatively, using more sophisticated deep learning architectures that may include attention-based networks or transformer networks that would enable better modeling of more complex interactions between images and tabular data could each be explored. Further, increased generalizability and robustness of the model could come from varying the cohort or from longitudinal data contributing to the dataset. In addition, real-time decision support and automated alert systems will have implications and value when the goal is clinical implementation. Furthermore, explainability and interpretability of outputs from the model would serve a new benefit to both medical practice and research in support of clinician trust and action on AI predictions. Each of these theoretical possibilities would complement the multimodal systems utilitarian future in precision medicine and postoperative outcomes prediction in spinal patients with diabetes. A limitation of the present study is that the experimental evaluation is conducted using a single-subject case for demonstration purposes. While this allows clear visualization of multimodal fusion and explainability mechanisms, future work will involve validation on larger, multi-center datasets to assess robustness, generalizability, and clinical reliability.

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