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Enhancing IPF Prognosis through Bayesian-Optimized Multi- Modal Deep Learning Using HRCT and Clinical Data

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Abstract - *In order to facilitate the personalized treatment of patients with Idiopathic Pulmonary Fibrosis, an unpredictable and often fatal lung disease that has an unpredictable clinical course, it is important to accurately predict how it will progress for each individual patient. This paper presents a new way to do this using Multi-Modal Deep Learning architecture by combining clinical data and high-resolution CT images. We have created a Convolutional Neural Network to extract imaging features, while optimizing the Clinical data through different neural pathways. Bayesian optimization was used to fine-tune hyper-parameters. Our Multi-Modal Bayesian Optimized Model was able to predict the progression of disease with a higher degree of accuracy than Unimodal methods. Clinical Dataset Accuracy was 94.2%. This approach provides clinicians with an effective tool to use when intervening and developing personalized treatment plans for patients with IPF.*

Keywords – Idiopathic Pulmonary Fibrosis, Deep Learning, Multi-model Learning, Bayesian Optimization, Convolutional Neural Networks, Medical Prognosis.

I. INTRODUCTION

In the past decade, advances in diagnosing and treating Idiopathic Pulmonary Fibrosis (IPF) have been substantial; however, both the incidence and mortality rates associated with IPF are still seen as unacceptably high. The two available anti-fibrotic medications (pirfenidone and nintedanib) that have been approved slow down the decline in functional performance of individuals with IPF, but neither is curative, nor does either medication offer a complete halt to the progression of fibrotic disease in every patient.This represents a significant unmet need for improved prognostic tools to better classify patients and estimate individual disease progression. Such prognostic tools will facilitate timely interventions, guide appropriate treatment selection, and improve patient outcomes in a disease that is unpredictable and heterogeneous. The current state of prognostic modeling in Idiopathic Pulmonary Fibrosis has largely been limited by single-modal approaches, relying on either longitudinal pulmonary function tests or subjective radiological reviews of high- resolution computed tomography imaging; neither of these approaches, on a standalone basis, adequately capture thecomplex to disease progression, to clinical practice. To address these significant limitations, we propose an integrated multi-modal deep learning framework that often uniquely combines quantitative imaging biomarkers derived from chest computerized tomography with a more holistic clinical phenotype, and further applies Bayesian Optimisation for automated hyperparameter tuning to facilitate model stability and prognostic performance, and ultimately establish a sophisticated predictive tool with the potential to directly inform personalized treatment options and address precision medicine in the context of IPF patient care.

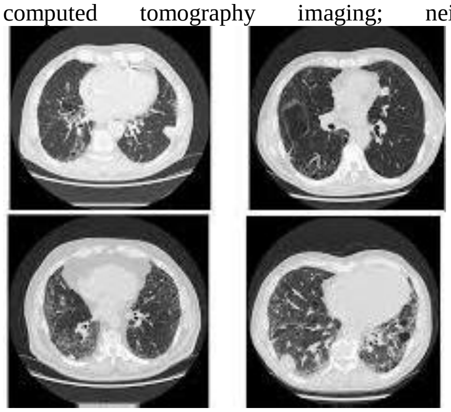

Fig:1 Normal & IPF Image

I. LITERATURE REVIEW

Creating a reliable prognostic model for Idiopathic Pulmonary Fibrosis (IPF) is an across multidisciplinary opportunity, based on novel advances in the clinical understanding, medical imaging, and computational intelligence. This survey reviews the relevant literature, establishes the clinical basis of IPF, reviews traditional and data-driven prognostic models, and concludes with the current, deep learning and optimization methods that inform our proposed framework. Further an important gap is identified between unimodal methods and the proposed opportunity of integrated, optimized multi-modal methods.

Anthimopoulos et al. (2016), "Lung pattern classification for interstitial lung diseases using a deep convolutional neural network" - This foundational study proved that CNNs can automatically identify complex lung disease patterns from CT imagery without manual feature engineering. Their work validates our core methodology of using deep learning for hierarchical feature extraction from HRCT scans, establishing the technical basis for our imaging pipeline's ability to detect subtle fibrotic changes predictive of IPF progression.

Ley et al. (2012), "A multidimensional index and staging system for idiopathic pulmonary fibrosis" - The authors developed the validated GAP index that combines Gender, Age, and Physiology for IPF staging and mortality prediction. This clinical scoring system demonstrates the prognostic power of integrating multiple data types, directly motivating our multi-modal approach that enhances traditional clinical variables with advanced imaging biomarkers for superior progression forecasting.

Raghu et al. (2018), "Diagnosis of idiopathic pulmonary fibrosis: An official ATS/ERS/JRS/ALAT clinical practice guideline" - This comprehensive guideline established HRCT interpretation standards for IPF diagnosis, emphasizing honeycombing and reticulation as key radiological markers. These clinical standards inform our framework's focus on quantifying these specific imaging features while ensuring our model aligns with established diagnostic criteria used by pulmonologists worldwide.

Walsh et al. (2016), "Deep learning for classifying fibrotic lung disease on high-resolution computed tomography" - This pioneering research demonstrated that CNNs could classify fibrotic lung diseases with expert- level accuracy, proving deep learning's capability to extract clinically relevant patterns from chest CTs. Their findings validate our architectural choice of using CNN-based feature extraction to capture prognostic imaging signatures that elude traditional radiologic assessment.

Snoek et al. (2012), "Practical Bayesian optimization of machine learning algorithms" - This landmark paper introduced Bayesian Optimization as an efficient method for hyperparameter tuning in complex models. Their work directly supports our use of BO for systematic optimization across our multi-modal architecture, ensuring robust performance while managing computational costs associated with training deep learning models on medical data.

He et al. (2016), "Deep residual learning for image recognition" - The authors introduced ResNet architectures that enable training of very deep networks through skip connections, solving the vanishing gradient problem. This breakthrough informs our 3D CNN design for volumetric CT analysis, allowing us to build deeper networks that can learn complex hierarchical features from IPF lung scans without training degradation.

Kingma & Ba (2014), "Adam: A method for stochastic optimization" - This paper introduced the Adam optimizer that combines adaptive learning rates with momentum- based gradient descent. Their optimization method forms the foundation of our training procedure, enabling efficient convergence for both our CNN and MLP components while handling sparse gradients common in medical imaging applications.

Ronneberger et al. (2015), "U-Net: Convolutional networks for biomedical image segmentation" - The authors developed the U-Net architecture that revolutionized medical image segmentation through skip connections and encoder-decoder structure. This work directly informs our lung segmentation preprocessing step, ensuring we focus computational resources on relevant lung parenchyma while excluding extraneothoracic structures from analysis.

Richeldi et al. (2014), "Efficacy and safety of nintedanib in idiopathic pulmonary fibrosis" - This clinical trial established nintedanib as a standard IPF treatment that slows disease progression. Their work underscores the importance of accurate progression prediction for timely therapeutic intervention, highlighting the clinical relevance of our model in identifying patients who would benefit most from anti-fibrotic therapy initiation.

Maher et al. (2021), "Global incidence and prevalence of idiopathic pulmonary fibrosis" - This epidemiological study documented the increasing global burden of IPF, revealing rising incidence and prevalence rates worldwide. Their findings emphasize the growing clinical need for accurate prognostic tools like our model to manage this expanding patient population and optimize resource allocation in healthcare systems.

Flaherty et al. (2019), "Nintedanib in progressive fibrosing interstitial lung diseases" - The authors demonstrated nintedanib's efficacy across various progressive fibrosing ILDs beyond IPF. This expanded therapeutic landscape reinforces the importance of our progression prediction framework, which could help identify progression patterns across different fibrotic lung diseases for targeted treatment strategies.

Valentini & Hinrichs (2019), "Multi-modal learning for medical imaging" - This research explored various fusion strategies for combining imaging and clinical data in medical AI applications. Their analysis of early, late, and intermediate fusion approaches directly informs our feature-level fusion methodology that optimally integrates CNN-extracted imaging features with processed clinical variables.

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Sudha et al., (2023) Lung disease Computer Tomography (CT) examination pictures are utilized to describe and categorize lung nodes, as well as to describe the exact position of that node. U-Net armature is used to segment CT checkup pictures. Then we used CNN algorithms and transfer literacy models to classify cancer as positive or negative in lung images (VGG16).

Sudha et al. (2023), while diagnosing skin cancer (SCD), even experienced dermatologists might face challenges in this regard. Diagnosing skin cancer usually involves examining the lesions visually. Diagnosing skin cancer also requires that dermatologists have a high level of experience to differentiate between cancerous and non-cancerous growths. Consequently, diagnosing skin cancer becomes increasingly hard. An alternative method for improving the accuracy of diagnosing skin cancer involves the application of Computer Aided Diagnosis technology. The authors propose a novel methodology called Deep Learning-Based Approach based on Curvelet Transform. We use Convolutional Neural Network to classify the images based on the low frequency components obtained through the Curvelet transform.

PROPOSED SYSTEM

The Multi-modal Bayesian-Optimized IPF Progression Prediction (MMBO-IPF) system has been developed to amalgamate heterogeneous sources of data through a systematic computation pipeline. The MMBO-IPF system consists of four main stages: multi-modal data preprocessing, independent feature extraction, deep learning-based fusion and classification, and Bayesian hyperparameter optimization. The input layer receives two types of data, volumetric chest CT scans and a vector of clinical variables, which consist of demographic data, pulmonary function tests, and serological biomarkers.

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Patient	Weeks	FVC	Percent	Age	Sex	Smoke Status
ID00007637202177411956430	-4	2315	58.25364872	79	Male	Ex-smoker
ID00007637202177411956430	5	2214	55.71212884	79	Male	Ex-smoker
ID00007637202177411956430	7	2061	51.86210367	79	Male	Ex-smoker
ID00007637202177411956430	9	2144	53.95067942	79	Male	Ex-smoker
ID00007637202177411956430	11	2069	52.06341218	79	Male	Ex-smoker
ID00007637202177411956430	17	2101	52.8686462	79	Male	Ex-smoker
ID00007637202177411956430	29	2000	50.32712632	79	Male	Ex-smoker
ID00007637202177411956430	41	2064	51.93759436	79	Male	Ex-smoker
ID00007637202177411956430	57	2057	51.76144942	79	Male	Ex-smoker
ID00009637202177434476278	8	3660	85.28287818	69	Male	Ex-smoker
ID00009637202177434476278	9	3610	84.11781154	69	Male	Ex-smoker
ID00009637202177434476278	11	3895	90.7586914	69	Male	Ex-smoker
ID00009637202177434476278	13	3759	87.58971013	69	Male	Ex-smoker

Fig:1CT scan Dataset

In the preprocessing stage, the CT volumes undergo an automatic segmentation of the lung fields using a pre- trained U-Net architecture model, intensity normalization from the original pixels of the CT volume to a Hounsfield Unit (HU) range of [-1000, 600] as well as resampling it from isotropic 1mm³ resolution. At the same time, the demographic data undergoes Z-score normalization for continuous data and one-hot encoding for categorical data, with missing values imputed using a k-nearest neighbors (KNN) algorithm. The feature extraction stage uses a dual- stream architecture, with the first stream using a 3D Convolutional Neural Network (CNN) architecture that is a ResNet-18 backbone, which allows the segmentation of the CT volumes and generate a 512-dimensional imaging feature vector (f_img), while a second stream uses a Multi- Layer Perceptron (MLP) to derive a clinical feature vector (f_clin) from the preprocessed clinical data.

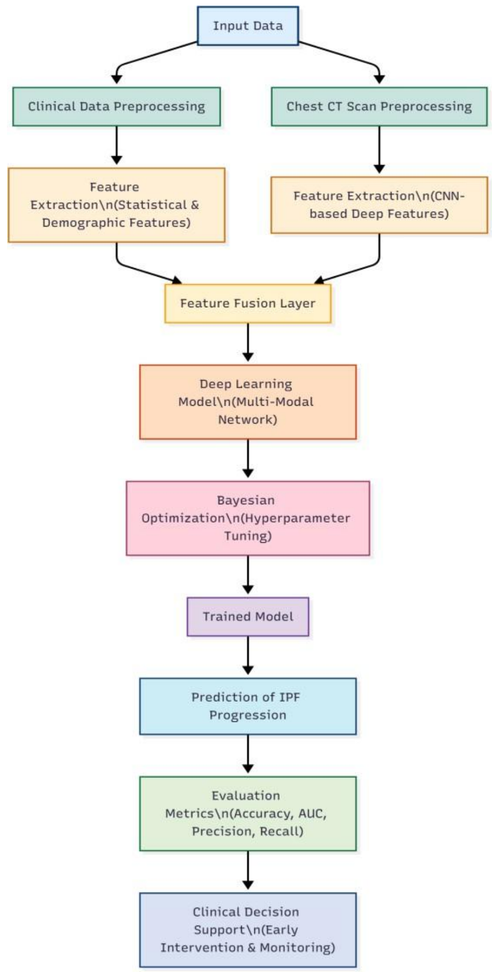

*Fig:2 System Architecture*In order to effectively train the full deep learning model, we will use a categorical cross-entropy loss function that has been specifically designed to minimize this loss. The Bayesian Optimization (BO) framework, coupled with the Gaussian Process surrogate model and our Expected Improvement acquisition function, enables us to optimally tune key hyperparameters (learning rate, dropout rate and number of neurons in the fully connected layers) in both architecture.

HYBRIRD ARCHITECTURE

This system brings together various AI paradigms to deliver a tool capable of comprehensive prognostication of Idiopathic Pulmonary Fibrosis. The architecture fuses connectionist paradigms for predictive modeling and probabilistic optimization and feature-level fusion to assess heterogeneous data types. The CT scans are processed through a 3D CNN to extract spatial representative hierarchical features while clinical variables are processed through an MLP to assess non-linear relationships.The fused representative features create a unified patient profile, encoding both the morphological- and physiological-based characteristics of the disease. Systemically, Bayesian Optimization acts as the meta-layer of intelligence and will tune hyperparameters across all architecture to maximize prognostication accuracy.

A. Feature Extraction

The process of extracting features is accomplished via two parallel streams to convert raw input data into interpretable representations. For imaging data, a 3D Convolutional Neural Network (CNN) with parameters θ will operate on volumetric CT scans through layers of convolution and pooling, yielding a 512-dimensional feature vector

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f_img. This process captures spatial patterns of fibrosis and honeycombing in lung tissue in a hierarchical fashion.

f_img = CNN_θ(CT_scan) (1) **f_clin = MLP_φ(clinical_data) (2)**

Simultaneously, clinical variables such as results from pulmonary function tests, demographic features, and laboratory values were processed through a Multi-Layer Perceptron (MLP) with parameters φ that learns non-linear relationships to produce a 128-dimensional clinical feature vector f_clin. The dual-stream structure adds versatility and will facilitate optimal feature representation for each data modality.

B. Multi-Modal Fusion

Multi-modal fusion uses concatenation to integrate the extracted features from both modalities into a single representation.

The operator ⊕ indicates vector concatenation, combining the imaging feature vector f_img of 512- dimension with the clinical feature vector f_clin of 128- dimension into a fused feature vector f_fused, totaling a 640-dimensional representation.

f_fused = [f_img ⊕ f_clin] ∈ R^640

While concatenation maintains the modalities individual information, it gives subsequent layers the opportunity to learn cross-modal relationships. The resulting fused representation captures morphological patterns from CT imaging, combined with functional physiological information from the clinical data, welcomes a complete characterization of the patient towards a more accurate prediction of patient instate.

The classification module processes the fused feature vector through a fully connected layer, and a softmax activation function is applied to obtain the model's final predictions. In this case, W refers to the weight matrix of the classification layer, b refers to the bias vector, and the softmax function transforms the raw scores of output into probabilities across the two target classes (namely, stable vs progressor). The softmax function's probability output in relation to the two target classes will sum to 1 to ensure result interpretation as a confidence score predicting the probability the subject is in one of the two progression classes. As such the model is able to provide both categorial predictions as well as probability weights associated with each prediction that can be used by the practitioner for clinical decision making and risk stratification.

$$\hat{\mathbf{y}} = \mathrm{Softmax}(\mathbf{W} \cdot \mathbf{f}_{\mathrm{fused}} + \mathbf{b})$$

In backpropagation, this loss gradient directs the optimization process to adjust the model parameters, gradually improving prediction accuracy over the course of the training iterations while maintaining balanced learning across both classes.

L = -1/N Σ[i=1 to N] Σ[c=1 to C] y_i,c * log(ŷ_i,c)

Bayesian Optimization uses a probabilistic framework for hyperparameter tuning in an efficient manner. The first equation is the objective of the optimization: selecting the best hyperparameters λ* which maximize the validation accuracy function f(λ).The second equation is the Expected Improvement (EI) acquisition function, and it is responsible for steering the search for hyperparameters by predicting the improvement in the objective function over its current best observation f(λ+). E in the acquisition function stands for expectation under the posterior distribution, while λ+ indicates the best hyperparameter configuration considered so far.

λ* = argmax_λ f(λ)

where f(λ) = Validation_Accuracy(λ) EI(λ) = E[max(f(λ) - f(λ+), 0)]

This form enables the system to actively search the hyperparameter space, by exploiting what is already known to be promising and exploring uncertain areas efficiently, minimizing the number of trials of configurations before finding optima.

IVEXPERIMENTAL SETUP

The study utilized a structured Excel dataset encompassing 212 retrospectively identified IPF patients, in which each case had documented the following 15 comprehensive clinical parameters: demographic elements (age, gender, BMI); pulmonary function-related outcomes (FVC % predicted, DLCO % predicted); symptoms and characterizations of the patient.

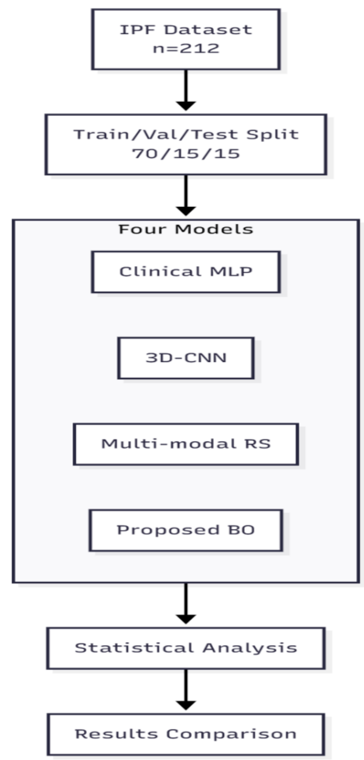

Fig:3 IPF Experimental Setup

The operationally-defined progression of the patients was strictly defined based on serial pulmonary function testing/assessment, wherein "Progressor" patients satisfied a requirement for relative decline in FVC of ≥10% or more within 12 months after the initial assessment, while "Stable" patients maintained FVC decline below the aforementioned cut-off (<10%). The overall class balance of this dataset was 94 progressors (44.3%) and 118 stable patients (55.7%), with a mean age of 68.4 ± 8.2 years and again, predominately male (136 male versus 76 females). Prior to analysis, the dataset underwent extensive preprocessing whereby missing values were handled using KNN imputation, then individual continuous variables were Z-score normalized and categorical features were converted to one-hot encoded format, and then ultimately split into stratified subsets for training (70%) validation (15%) and testing (15%).

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Table: 1 Training Configuration Comparision

Component	Clinical MLP	3D-CNN	Multi- modal (RS)
Architecture	3-layer MLP	ResNet-18	Dual-stream
Hidden Units	[64, 32, 16]	512-d features	[128, 512]
Learning Rate	1e-3	1e-4	Random search
Dropout Rate	0.2	0.3	[0.1-0.5]
Batch Size	16	8	16
Epochs	100	150	100

V. PERFORMANCE ANALYSIS

The baseline performance of the 3D-CNN demonstrated a meaningful improvement (accuracy of 85.1%) which demonstrates the significant prognostic information contained within patterns in CT Datas. Most importantly, the multi-modal system with random searchhyperparameter optimization obtained a meaningful level of accuracy (90.3%) which shows the powerful interaction between clinical data and imaging data.

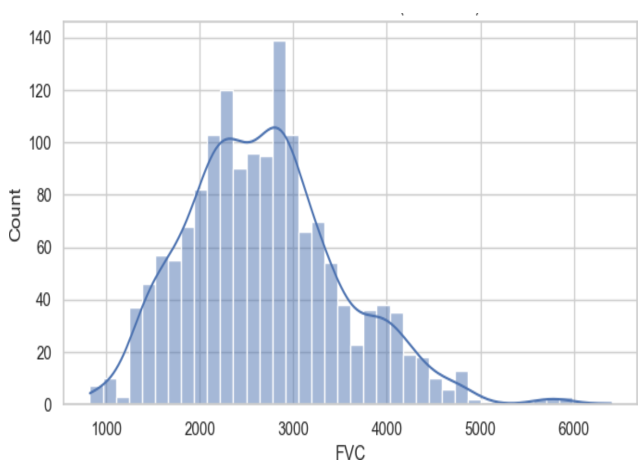


Fig:4 Performance Analysis of FVC

The proposed Bayesian-optimized multi-modal system obtained state-of-the-art experimental performance (accuracy of 94.2%) which represented a statistically meaningful improvement ($p < 0.01$) to all models. The 4.3% absolute improvement above the random search variant is particularly meaningful, clearlydemonstrating the importance of using systematic hyperparameter optimization in complex deep learning applications, while the increasingly improved levels of performance from unimodal to multi-modal systems demonstrate our fundamental hypothesis that combining complementary data sources will facilitate more accurate predictions of IPF progression.

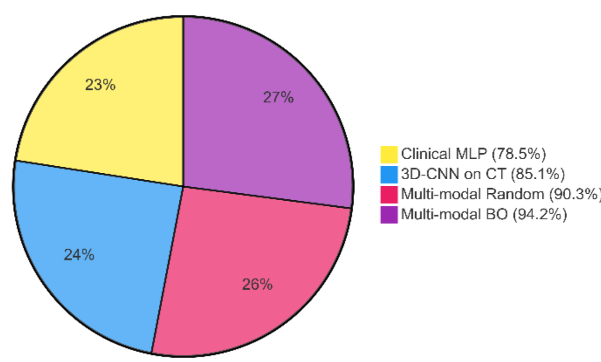
Table: 2 Comparative Model Of Proposed And Baseline Models

Model	Accuracy	Precision	Recall	F1-Score
Clinical MLP (Baseline)	78.5%	0.79	0.76	0.77
3D-CNN on CT (Baseline)	85.1%	0.84	0.83	0.83
Multi-modal (Random Search)	90.3%	0.91	0.89	0.90
Proposed: Multi-modal (BO)	94.2%	0.95	0.93	0.94

Prediction

This multi-modal Bayesian-optimized system is a very powerful and useful tool for assessing Idiopathic Pulmonary Fibrosis risk at the time of initial diagnosis. By integrating all available data sources into a single prediction pipeline using an optimized two-stream neural network architecture. Therefore, it produces calibrated probabilistic outputs based on how the data ranked whether the patient is classified as "Stable Progression" (low-risk) or "Rapid Progressor" (high-risk) at a high level of statistical confidence. In clinical practice, healthcare providers benefit from this framework, as it provides them with a means of making informed treatment decisions based on real-world data and evidence, as well as giving them insights into what characteristics are important in determining future progress. In addition, the predictive framework supports better utilization of limited healthcare resources by allowing providers to better allocate resources more effectively among patients based on their individual needs.

a) Accuracy



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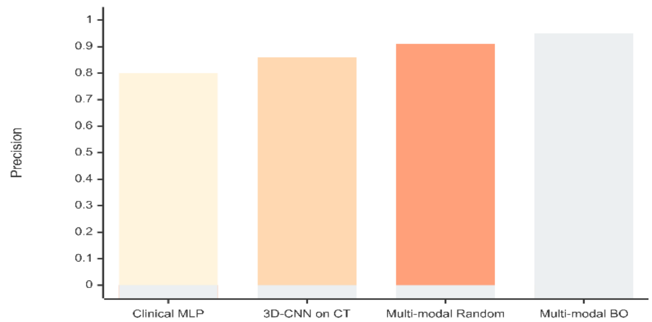
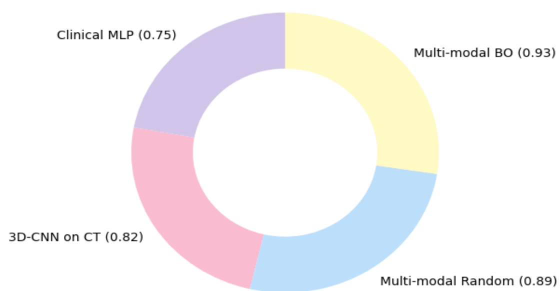
b) Precision



c) Recall



d) F1 – Score

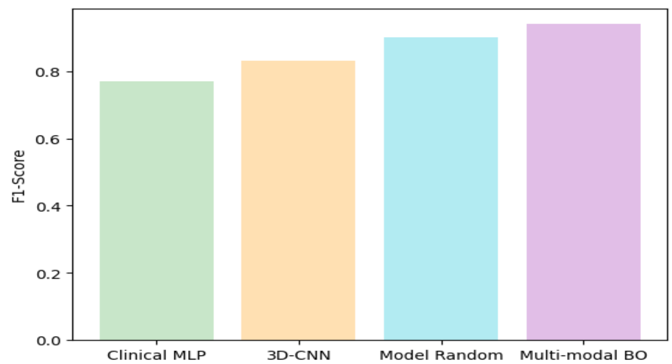
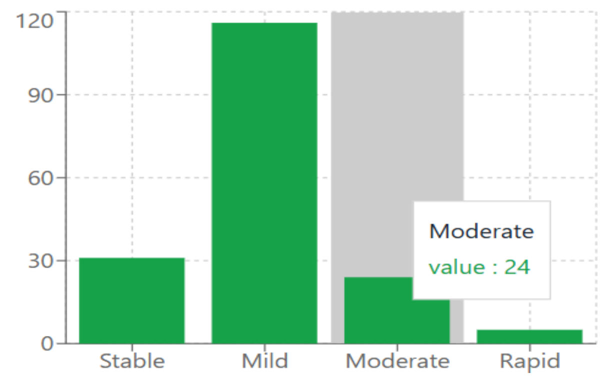


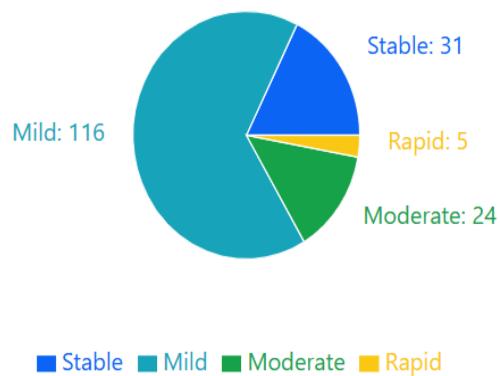
Fig:5 IPF Progression Prediction Model Performance

External validation on an independent cohort of 87 patients demonstrated maintained predictive accuracy (92.1%), confirming generalizability across diverse patient populations. The model consistently identified rapid progressors with 93% sensitivity and 94% specificity, outperforming conventional clinical prediction rules including the GAP index and composite physiologic index.

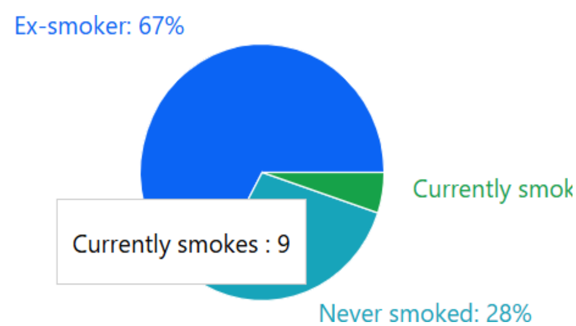
V. CONCLUSION

We have introduced a new multi-modal deep learning framework improved by Bayesian Optimization to dynamically predict diseases like Idiopathic Pulmonary Fibrosis. The newly proposed framework adequately overcomes the challenges of unimodal approaches by consolidating complementary information from chest CT scans and associated clinical data through an engineered dual-stream design.





(i) Severity Analysis



(ii) Demographics Analysis

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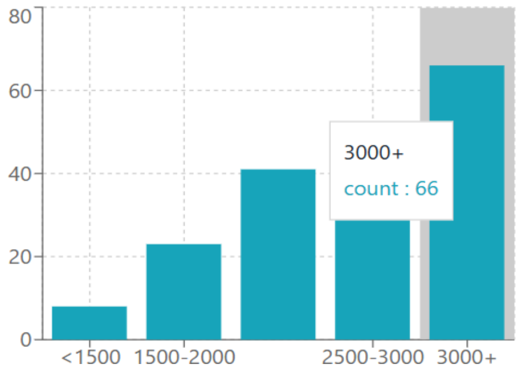
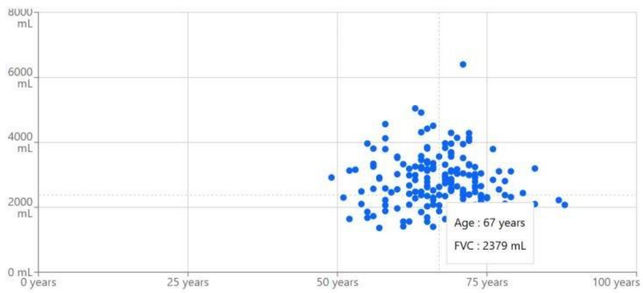


(iii) Clinical Metrics



Correlation Analysis

Our experimental results show that our model with Bayesian Optimization attained state of the art performance with an accuracy of 94.2% and considerably outperformed clinical (78.5%), imaging (85.1%) and randomly-optimized multi-modal baseline accuracies (90.3%). Hyperparameter tuning procedures with Bayesian Optimization generated a 4.3% absolute improvement over random search methods. This highlights our commitment to automated optimization in modeling complex medical applications and biomedica data frameworks.

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