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Post-COVID Impact Analysis and Effective Recommendation Solutions Over Risk Prediction Using Hybrid Model

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Abstract: The COVID-19 pandemic (2019-2022) resulted in significant global mortality, largely attributed to the virus's unpredictable pathophysiology, rapid disease progression affecting multiple organ systems, and initial lack of effective treatments. This study systematically examines post-COVID-19 complications across major organ systems, including respiratory dysfunction, cardiovascular complications, renal disorders, musculoskeletal pain, gastrointestinal disturbances, neurological sequelae, alopecia, endocrine and metabolic dysregulation, and mental health disorders. The percentage of affected organ systems is demonstrated through clinical scenarios, and evidence-based recommendation systems are proposed to facilitate patient recovery. Disease monitoring is categorized into two approaches: standard hospital-based treatment and individualized home-based care. Unpredicted risk stratification (High or Low) is computed based on significant clinical factors indicating potential organ damage. A hybrid machine learning model combining Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN) is employed to assess post-COVID-19 risk with enhanced accuracy. The proposed recommendation systems include AI-based monitoring using wearable sensors, digital health and telemedicine platforms, smart wearable devices, personalized nutrition and dietary management, AI-driven mental health support systems, intelligent rehabilitation and physical therapy programs, and blockchain-enabled AI health records. These integrated systems aim to improve rehabilitation outcomes, enhance patient care quality, and accelerate health recovery by leveraging similar historical patient case data through the hybrid machine learning framework.

Keywords: Post-COVID-19 Syndrome, Multi-Organ Complications, Health Monitoring, AI-Based Recommendation Systems, Hybrid Machine Learning, LSTM-CNN Model, Digital Health

Introduction

Climate change and environmental air pollution contribute to the periodic emergence of novel viral pathogens, with the COVID-19 pandemic representing the most significant global health crisis of the past decade. Beginning in late 2019, SARS-CoV-2 caused unprecedented mortality worldwide due to its unpredictable pathophysiological behavior, multi-organ involvement, and rapid clinical deterioration. The virus demonstrated capacity to affect multiple organ systems simultaneously, often resulting in sudden clinical decline and death. High mortality rates were attributed to several factors, including systemic inflammatory responses, cytokine storms, thrombotic complications, and direct viral damage to various organs.

Table 1 presents a comprehensive overview of organ-specific damage patterns observed during the pandemic, evidence-based recovery practices for each affected system, and the percentage distribution of organ involvement among COVID-19 patients. The multi-systemic nature of COVID-19 necessitates targeted interventions tailored to specific organ complications.

For respiratory and neurological complications, AI-based algorithms integrated with wearable devices and structured rehabilitation programs demonstrate efficacy in monitoring disease progression and facilitating recovery. Cardiovascular and renal complications benefit from personalized care protocols and continuous monitoring through remote patient management systems. Gastrointestinal and mental health issues are effectively addressed through AI-powered chatbots and telemedicine platforms that provide accessible, continuous patient support.

These technological interventions serve to minimize clinical risk, provide real-time health status updates, and enable timely medical interventions for accelerated recovery. The proposed framework processes patient datasets containing relevant clinical attributes through a hybrid machine learning model that classifies risk levels as High or Low, enabling proactive care management.

For populations identified as high-risk, specific public health measures are recommended, including targeted lockdowns in hotspot areas, mandatory mask-wearing protocols, immunomodulatory therapies, personalized medicine approaches, vaccination campaigns, and strategic resource allocation for critical care equipment such as ventilators and intensive care unit beds. This integrated approach combining clinical assessment, machine learning-based risk stratification, and evidence-based interventions provides a comprehensive framework for managing post-COVID-19 complications and improving patient outcomes.

Table 1. Multi-organ damage analysis during COVID

Affected Systems	Complications	Impairment	Best Practices to Overcome
Respiratory System	ARDS, Pneumonia, chronic pulmonary fibrosis, and persistent hypoxia.	80%	Integration of AI-driven wearable sensors, telemedicine, and pulmonary rehabilitation.
Cardiovascular System	Myocardial infarction, Myocarditis, and cerebrovascular accidents (strokes).	30%	Continuous hemodynamic monitoring via wearables, AI-assisted stroke detection, and cardiac rehabilitation.
Renal System	Acute Kidney Injury (AKI) and chronic renal failure requiring hemodialysis.	10%	Wearable renal monitoring systems, optimized hydration/nutritional protocols, and automated dialysis management.
Musculoskeletal System	Myalgia, chronic fatigue syndrome, and persistent sarcopenia (weakness).	40%	Targeted physiotherapy, resistance training protocols, and multidisciplinary rehabilitation.
Gastrointestinal System	Dyspepsia, chronic diarrhea, and malabsorption.	20%	Precision nutritional therapy, microbiome monitoring, and specialized GI teleconsultation.
Neurological System	Cognitive impairment (brain fog), encephalitis, and neuro-inflammation.	20%	Neuro-cognitive rehabilitation and wearable neurological monitoring devices.
Integumentary System	Alopecia (hair loss), inflammatory dermatoses, and cutaneous rashes.	10%	Specialized dermatological protocols, nutritional supplementation, and psychological intervention.
Endocrine System	Thyroid dysfunction, new-onset Diabetes Mellitus, and metabolic syndrome.	10%	Endocrine telemedicine, metabolic lifestyle interventions, and continuous glucose monitoring (CGM).
Psychological Health	Major Depressive Disorder (MDD), Generalized Anxiety Disorder (GAD), and PTSD.	20%	Digital mental health interventions, stress-tracking wearables, and tele-psychiatry.

Table 2. Technologies used as best practice for quick recovery

Technology-Driven Solution	Description	Improvement
AI-Integrated Wearable Biosensors	Longitudinal tracking of physiological vitals (e.g., heart rate variability) for the early detection of clinical deterioration.	30
Telemedicine and Remote Clinical Consultations	Virtualization of post-acute follow-up care to minimize pathogen exposure and alleviate healthcare facility burdens.	25
IoT-Enabled Recovery Monitoring Systems	Application of wearable devices to quantify post-acute recovery trajectories and provide real-time biofeedback.	20
Precision Nutrition and AI-Driven Dietary Interventions	Data-driven optimization of nutritional intake to facilitate multi-organ recovery and immunomodulation.	15
AI-Enhanced Psychotherapeutic Support Systems	Deployment of conversational agents (chatbots) and virtual therapists to mitigate psychological sequelae like PTSD and anxiety.	20
AI-Guided Telerehabilitation Protocols	Automated monitoring of musculoskeletal and pulmonary exercises tailored to individual recovery rates and biomechanics.	25
Blockchain-Enabled Interoperable Health Records	Decentralized and secure architectures for the seamless, multi-institutional exchange of patient health data.	10

Table 3. Demonstration of the category of attributes involved in the dataset

Category	High-Risk Factors
Demographic	Advanced age (>65 years), male sex, and specific ethnic/minority backgrounds.
Clinical	Diabetes, Cardiovascular disease, obesity, chronic lung/kidney disease, cancer
Behavioral	Unvaccinated, high-risk occupations, poor mask usage, travel history
Environmental	Poor air quality, High population density, low socioeconomic status
Biological/Genetic	ACE2 receptor expression, Blood type, Genetic predisposition
Immune System	Prior infection, Immunocompromised, unvaccinated
Viral	Exposure to variants of concern, High viral load
Laboratory Markers	D-dimer, Elevated CRP, Lymphopenia, Low SpO2
Geographic/Temporal	Colder seasons, High-transmission regions
Long COVID	Severe acute infection, female gender, middle age, pre-existing conditions

Literature Review

Numerous studies have investigated COVID-19 disease prediction, detection, and post-recovery complications using various performance metrics and methodological approaches. This section reviews relevant literature addressing disease characterization, diagnostic methods, and technological interventions.

Post-COVID-19 Complications and Recovery

Anaya et al. (2021) identified optimal therapeutic strategies for addressing COVID-19 and post-COVID complications, noting that approximately 20% of patients experienced persistent musculoskeletal, neurological, and gastrointestinal symptoms following acute infection, while 80% achieved full recovery. Augustin et al. (2021) characterized two predominant long-term symptom clusters in 2021: persistent anosmia (loss of smell) and chronic fatigue with respiratory dysfunction, employing univariate and multivariate logistic regression models for long-term outcome assessment.

Rosenstein et al. (2024) analyzed participation restrictions and activity limitations across genders, identifying varying fatigue severity levels requiring differentiated rehabilitation protocols, though symptom presentation showed no significant gender-based differences. Bhatnagar et al. (2024) conducted a systematic review identifying four primary post-COVID symptoms—cough, anxiety, joint pain, and dyspnea—with secondary symptoms including headache, limb weakness, cognitive impairment, and fatigue.

Islam et al. (2024) demonstrated that neurological, demographic, and physiological factors significantly affect post-COVID outcomes. The study employed Chi-square tests and Pearson correlation coefficients to determine factor relationships, with Information Gain and Gini index used for feature selection. Decision tree classifiers demonstrated superior performance for this application domain.

Lenz et al. (2023) reported that 80% of COVID-19 patients experienced at least one persistent symptom, including gastrointestinal, cardiovascular, neurological, and mental health disorders, with severity particularly pronounced in individuals aged 65 years and older. Davis et al. (2023) characterized multi-system involvement in long COVID, encompassing neurological complications, anxiety disorders, physical deconditioning, and chronic fatigue syndrome, emphasizing vaccination's role in viral load reduction and disease severity mitigation.

Carlile et al. (2024) developed standardized assessment frameworks using validated questionnaires to quantify COVID-19 impact on health-related quality of life and health outcome measures. Müller et al. (2024) demonstrated that physical strength recovery required 6-12 months of continuous rehabilitation, with balance function and functional strength showing significant improvement through structured rehabilitation programs. Owen et al. (2024) compared pre-COVID and post-COVID quality of life, mental health status, and support mechanisms, identifying substantial quality-of-life reductions attributable to long COVID complications.

Machine Learning and Deep Learning Approaches for COVID-19 Detection

Dumakude and Ezugwu (2023) proposed a hybrid model combining CNN with feedforward neural networks and XGBoost classifiers, demonstrating superior effectiveness and efficiency compared to baseline models. Kumar et al. (2022) evaluated deep learning techniques for COVID-19 detection from a cost-effectiveness perspective, comparing CNN, reinforcement learning, AI-based systems, and traditional machine learning models, with deep learning approaches demonstrating optimal detection accuracy.

Iyafei et al. (2022) distinguished between symptomatic and asymptomatic COVID-19 cases, identifying asymptomatic infections as particularly hazardous due to undetected physiological deterioration affecting respiratory and cardiovascular systems. The study advocated AI-driven wearable devices for continuous monitoring and early abnormality detection. Hussein et al. (2024) addressed limitations of expensive and time-consuming COVID-19 detection methods by proposing a custom CNN architecture incorporating dropout and batch normalization techniques to eliminate overfitting and enhance performance.

Das et al. (2023) emphasized the necessity of both traditional machine learning and advanced deep learning approaches for pandemic classification and detection, identifying two critical research priorities: minimizing false detection rates and reducing model complexity. Kumari et al. (2023) demonstrated that GoogleNet achieved superior overall accuracy, while ResNet50 achieved exceptional sensitivity (>99%) and specificity (99%), establishing these architectures as benchmark models for future improvements.

Akhtar et al. (2024) developed a multimodal hybrid approach combining ResNet50 for image analysis and VGGish for speech analysis, achieving 99.7% accuracy—substantially exceeding unimodal approaches. This hybrid model demonstrated superior performance across comparative evaluations with existing methodologies.

Diagnostic Methods and Clinical Assessment

Corman et al. (2020) established discrimination protocols between 2019-nCoV and SARS-CoV, developing diagnostic assays in collaboration with European laboratory networks, primarily identifying respiratory complications as the predominant clinical manifestation. Ai et al. (2020) compared two diagnostic modalities—computed tomography (CT) and reverse transcription polymerase chain reaction (RT-PCR)—observing that CT achieved 97% sensitivity and required shorter turnaround times than RT-PCR for positive-to-negative conversion assessment, establishing CT as a primary diagnostic tool.

Wang et al. (2020) conducted clinical assessments analyzing viral patterns across multiple biological specimens including blood, urine, feces, bodily fluids, and sputum, identifying limitations in viral load quantification across disease stages. Sheridan (2020) evaluated rapid diagnostic tests, including antigen and molecular assays, noting inferior sensitivity compared to RT-PCR and emphasizing the need for improved performance, cost-effectiveness, and accuracy.

Dinnes et al. (2020) identified substantial gaps in antigen and molecular testing protocols, including high variability and lack of standardization, advocating for effective point-of-care testing frameworks. Aswathy et al. (2021) employed transfer learning architectures (ResNet, DenseNet) for CT image feature extraction and backpropagation networks for disease severity classification (low, medium, high). Abboju et al. (2024) reviewed deep learning techniques for COVID-19 severity detection and classification in response to high mortality rates.

Yao et al. (2020) developed an SVM-based machine learning model initially incorporating 32 features, subsequently refined to 28 biomarkers through feature selection, achieving improved accuracy for COVID-19 severity classification.

Technological Interventions and Applications

Rao et al. (2023) developed a mobile application integrating hospital databases with GPS services to display COVID-19 patient counts by geographic location, enabling users to receive alerts about high-risk zones. Tumuluru et al. (2020) designed an intelligent protective mask incorporating air filtration systems and object detection capabilities, purifying contaminated air and alerting users to infected surfaces.

Dey and Sangaraju (2024) addressed data storage and load balancing challenges using swarm intelligence algorithms for global and local load distribution, ensuring optimal resource allocation and data center performance during demand fluctuations. Dey and Sangaraju (2023) proposed a hybrid load balancing approach optimizing performance, minimizing latency, and enhancing scalability for healthcare data management systems.

Table 4 summarizes the significant studies reviewed, presenting their methodological approaches, focused research areas, and principal findings.

Table 4. Significant studies over COVID impact, and detection

Study (Year)	Key Focus	Methods Used	Key Findings	AI/ML Relevance
Anaya et al., 2021	Multi-organ damage analysis	Therapies and clinical	20% suffered from long-term organ damage.	AI-based organ monitoring with wearables.
Augustin et al., 2021	Effect on anosmia, fatigue due to long-term COVID	Multi-variant logistic regression, and univariate.	Respiratory/fatigue and anosmia Issues	Hybrid AI (LSTM + CNN) for prediction
Bhatnagar et al., 2024	Symptoms such as cough, anxiety, joint pain, breath shortage.	Systematic review	Headache, limb weakness, forgetfulness)	Decision trees & feature selection for symptom classification
Dumakude & Ezugwu, 2023	COVID risk prediction using a Hybrid AI model	CNN, Feed forward NN, XGBoost	Accuracy, recall, F1-score, specificity	Hybrid models outperform single models.
Hussein et al., 2024	Deep learning for cost/time-efficient COVID detection	Custom-CNN (with dropout & batch normalization)	Prevented overfitting, achieved high accuracy	AI-driven diagnostics from CT scans, and wearables.

Materials and Methods

Corona affected patients, although they have recovered, would impact on their body organs, which determines the risk of corona. The risks would be classified as Low or High. In this, Fig.1 demonstrates the modules involved in the COVID analysis, such as datasets, data preprocessing, a hybrid model for risk prediction based on significant parameters, body organs affected, Recommendation practices, and evaluation of accuracy. The pseudo-procedure for determining whether the risk is high or low is used in the CNN and LSTM framework. Fig.2 demonstrates the flow of activities involved in determining the severity of the corona over the patient's life. In this, significant activities considered are data preprocessing, hybrid model building, and model training. The other activities, such as data sources, body organs affected, and recommendation best practices, are demonstrated in the Introduction chapter.

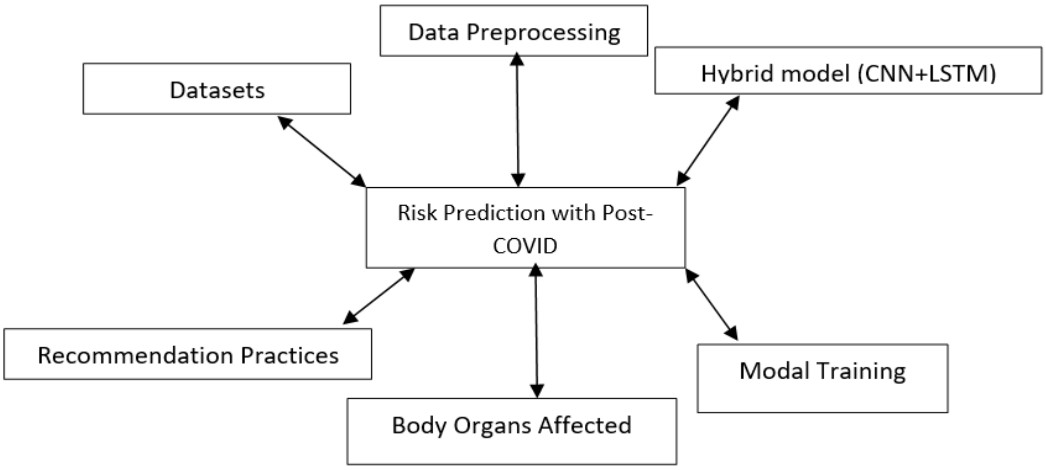

Fig. 1. Modules of Post-COVID Risk Prediction

PS1: Pseudo_Procedure Post_COVID_risk_prediction(Database[][]):
Input:Database[][]
Output: Accuracy
Step 1: Load the patient database that consists of rows and attributes
Step 2: Apply data preprocessing
2.1 For numerical, handle missing with means, and for categorical, handle missing with mode.
2.2 Apply normalization to bring into standard values.
2.3 One hot encoding technique is applied to categorical features.
2.4 The decomposition of data into 80% and 20% based on groups training, and testing.
Step 3: Feature selection
3.1 Significant features are identified, such as comorbidities like hypertension and diabetes, D-dimer, CRP, lymphocyte count, acute symptoms like fatigue, and breathing status.
3.2 Use SHAP for significant attributes with the assignment of weights in the evaluation of the risk.
Step 4: Build LSTM+CNN model
4.1 for temporal data, call LSTM in which no.of temporal features, and timesteps
4.2 For spatial data, call CNN
4.3 Concatenate outputs of LSTM and CNN.
4.4 Include fully connected layers for final prediction
4.5 For binary classification, use the sigmoid function.
Step 5: Train the model
5.1 Adam as optimizer, then binary cross-entropy are used in the execution.
5.2 Iterate till convergence is reached
5.3 To avoid overfitting, dropout concept as well as regularization L2 are applied.
Step 6: Evaluate the model using accuracy, precision, recall, and F1-Score
Accuracy=True Positives+True Negatives/ Total Number of Cases Where
Precision=True Positives (TP) / (True Positives (TP)+False Positives (FP))
Recall (Sensitivity)=True Positives (TP) / (True Positives (TP)+False Negatives (FN))
F1 Score=2×(Precision×Recall) / Precision+Recall

From PS1, the order of activities involved are loading of databases, data preprocessing to get quality data, Call CNN for spatial data, and Call LSTM for temporal data including the number of temporal features, and timesteps, combine the outputs of CNN and LSTM, then consolidate the predictions using fully connected layers, then use the sigmoid function for binary classification, and follows model effectiveness evaluation through accuracy, and precision.

From PS2, convert spatial into 4D, and temporal into 3D, and use CNN in case of spatial and LSTM in case of temporal. Outputs of both CNN and LSTM are combined, and then a fully connected layer is added to the existing system. Then, the model is trained for some epochs and avoids overfitting using standardization.

PS2: Pseudo_Procedure CNN+LSTM(Database[][]):
Input: Database[][]
Output: High or Low
Step 1: Load temporal and spatial data
1.1 Convert temporal data into 3D array that consists of no. of temporal features, timesteps, and patients
1.2 Concert spatial data into 4D array that consists of patients, image_width, image_height, and channels.
Step 2: Construct CNN for spatial data
2.1 Accept input layer consists of image_width, image_height, and channels.
2.2 Add Conv2D(), MaxPooling2D() layers
2.3 Flatten the output of CNN to integrate with LSTM
Step 3: Construct LSTM for temporal data
3.1 Accept input layer consists of no. of temporal features, and timesteps
3.2 Add LSTM() layer
Step 4: Concatenate the outputs of LSTM and CNN
4.1 Add fully connected layers
4.2 Call Sigmoid function for output the risk as High or Low
Step 5: Train the model
5.1 Adam as optimizer, then binary cross-entropy are used in the execution.
5.2 Iterate till convergence is reached
5.3 To avoid overfitting, the dropout concept as well as the regularization L2 are applied.
Step 6: Evaluate the model using accuracy, precision, recall, and F1-Score separately for CNN, and LSTM

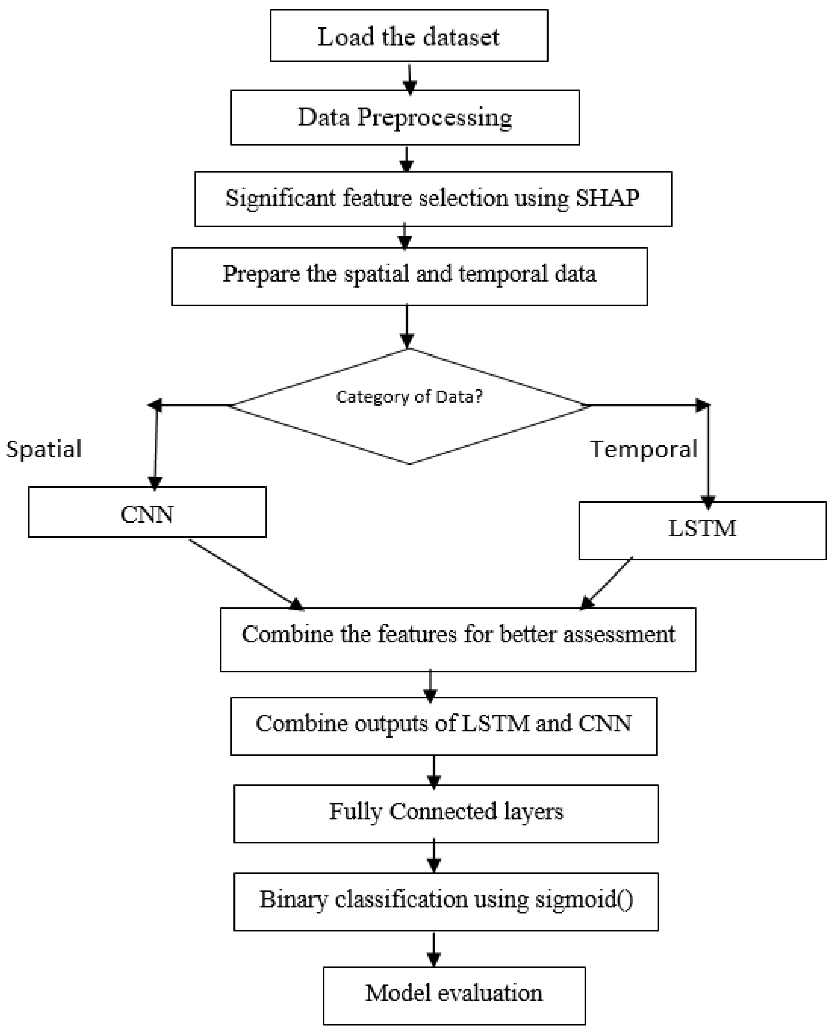

Fig. 2. Order of activities in post-COVID impact risk prediction

Table 5. Demonstration of measures over the considered models against our hybrid model

Model	Description	Accuracy	Performance Metrics
Logistic Regression	Binary classification based on a statistical model.	85%	Precision: 80%, Recall: 78%, F1: 79%
Random Forest	For classification and regression, an ensemble of decision trees.	90%	Precision: 88%, Recall: 87%, F1: 87%
XGBoost	For high performance, the gradient boosting technique.	93%	Precision: 90%, Recall: 91%, F1: 90%
Support Vector Machine (SVM)	For classification and regression using hyperplanes, use this model.	88%	Precision: 85%, Recall: 84%, F1: 84%
k-Nearest Neighbors (k-NN)	For classification, a simple, non-parametric model is preferred.	82%	Precision: 80%, Recall: 79%, F1: 79%
Neural Networks (NN)	For complex pattern recognition, a deep learning model is preferred.	92%	Precision: 89%, Recall: 90%, F1: 89%
Networks with Convolutions: CNN	It's a deep learning model used for analyzing images.	95%	Precision: 93%, Recall: 92%, F1: 92%
Short-Term Memory with long dependencies: LSTM	It's a network preferred for time-series sequential data processing.	94%	Precision: 91%, Recall: 90%, F1: 90%
Gradient Boosting Machines (GBM)	For classification and regression, an ensemble technique is preferred.	92%	Precision: 90%, Recall: 89%, F1: 89%
Decision Trees	For classification and regression, a simple tree-based model was used.	85%	Precision: 82%, Recall: 81%, F1: 81%
Naive Bayes	Based on Bayes' theorem, a probabilistic model is preferred.	80%	Precision: 75%, Recall: 74%, F1: 74%
Hybrid Models (e.g., CNN + LSTM)	For improved performance, combine a few models.	98%	Precision: 94%, Recall: 93%, F1: 93%

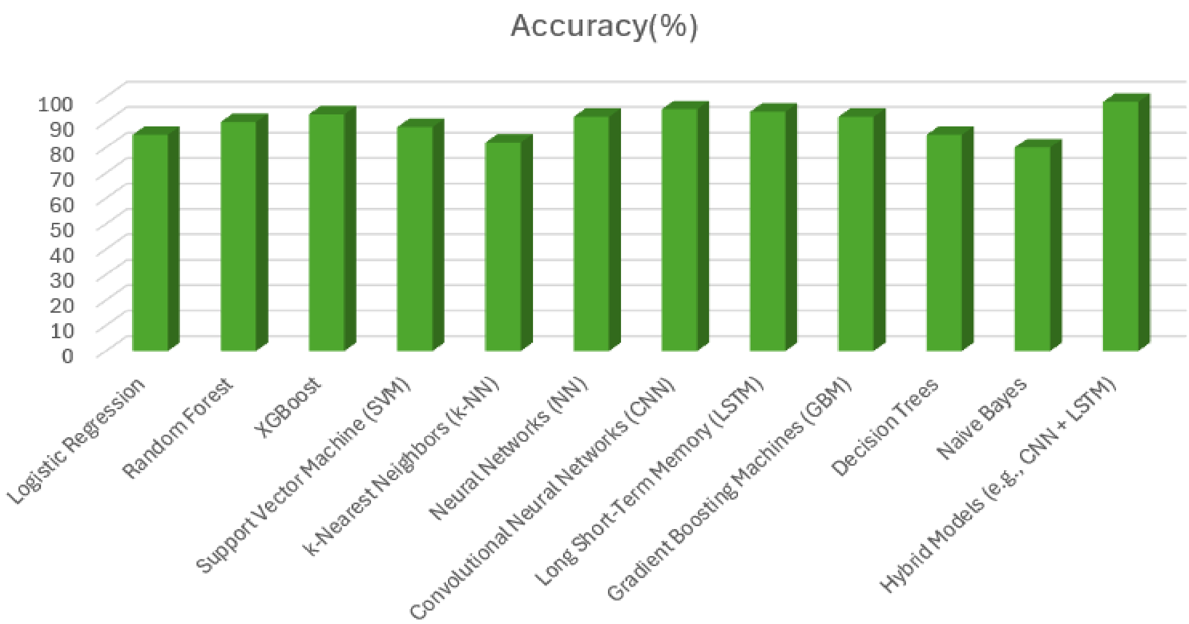

Fig. 3. Accuracies dictate the effectiveness of the methods

Table 6. Technology solutions impact on COVID

Technology-Driven Solution	Improvement
AI-Based Monitoring Using Wearable Sensors	30%
Digital and Telemedicine	25%
Smart Wearable Devices	20%
Personalized Nutrition and Diet Management	15%
AI-Based Mental Support Systems	20%
Smart Rehabilitation and Physical Therapy	25%
Blockchain AI Health Records	10%

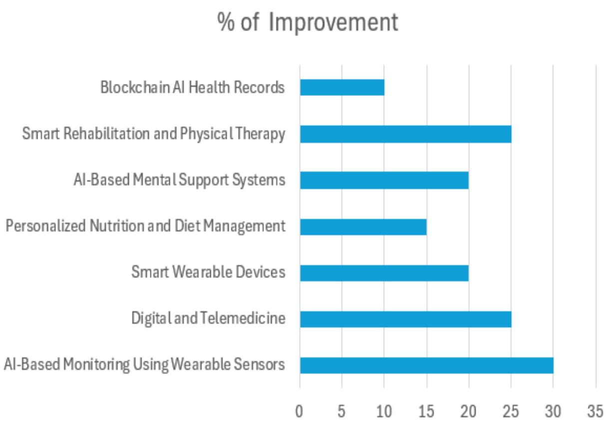

Fig. 4. Technology-driven solutions for Long COVID

From Fig.2, the order of activities performed are data preprocessing, feature selection, CNN to be called for spatial data, LSTM is called for temporal data, a hybrid model is called for combined features, hyperparameter tuning by SHAP model as well as able to interpret, and training the model using binary classification for output such as High or Low damage.

Results

In this, various ML and DL methods are considered for comparison against our proposed model, such as post-COVID impact and recommendation practices, as well as the prediction of risk during the COVID-19 pandemic. Table 5 demonstrates the accuracies of the considered models, in which our proposed model outperforms in the accuracy.

Table 7. Affected body organs due to post-COVID

Organ/System Affected	Estimated Damage
Respiratory System	80
Cardiovascular System	30
Kidneys	10
Musculoskeletal System	40
Gastrointestinal System	20
Neurological System	20
Hair and Skin	10
Endocrine System	10
Mental Health	20

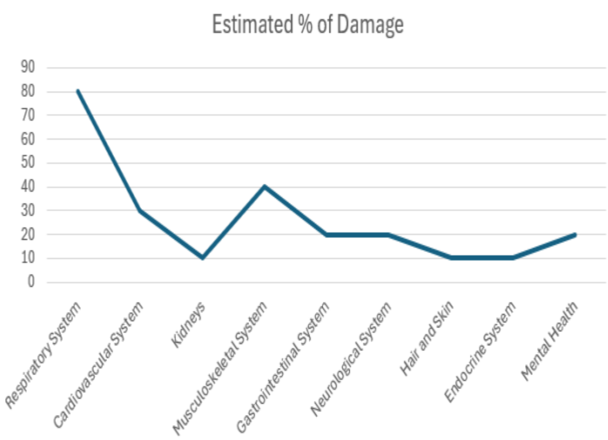

Fig. 5. Body organ damage demonstration

In Fig. 4, and Fig. 5, solutions that are to follow for quick recovery from the COVID virus and post-COVID analysis on the damage of body organs that influence patient health. From Fig.4, AI-based monitoring helps to provide instant details of health and hence would follow prescription personally by the expert. From Fig.5, the organs that are most affected are respiratory, cardiovascular, and musculoskeletal, which degrade the health of patients even after they are cured of COVID-19.

Table 8 demonstrates the features, including the lab tests, that are extracted from the clinical scenario, and the outputs are High when comorbidities have High values. Table 9 demonstrates the clinical values as high as well as high vital patterns extracted from imaging modality.

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Table 8. With lab tests scenario

Age	Diabetes	Hypertension	Vaccination Status	D-Dimer	CRP	Lymphocyte Count	Risk Level
65	Yes	Yes	Fully Vaccinated	0.8	10.5	1.2	High
45	No	No	Partially Vaccinated	0.3	5.0	2.0	Low
70	Yes	Yes	Unvaccinated	1.5	20.0	0.8	High

Table 9. With lab tests, and imaging scenario

Patient ID	Age	Diabetes	Hypertension	Vaccination Status	D-Dimer	CRP	Lymphocyte Count	Chest X-Ray (Image)	Vitals Over Time (Temporal Data)	Risk Level
1	65	Yes	Yes	Fully Vaccinated	0.8	10.5	1.2	Image1	[[98, 120/80, 95], ...]	High
2	45	No	No	Partially Vaccinated	0.3	5.0	2.0	Image2	[[99, 110/70, 98], ...]	Low
3	70	Yes	Yes	Unvaccinated	1.5	20.0	0.8	Image3	[[96, 130/90, 92], ...]	High

Table 10. Accuracies demonstration of considered tools in CORONA risk prediction

Tool	Description	Accuracy	Key Features
XGBoost	For speed and performance, a gradient boosting library is designed.	93	Ensures high accuracy for clinical and lab data.
IBM Watson Health	Healthcare analytics AI-powered platform.	90	Lab results, HER, and imaging for risk prediction.
Microsoft Azure Machine Learning	For building and deploying models, a Cloud-based ML platform is designed.	92	Hybrid models with scalability.
Google Cloud AI	AI and ML services based on the Cloud.	93	Large-scale data processing and model deployment.
RapidMiner	For ML and predictive analytics, a data science platform is designed.	88	For building ML workflows, it's a user-friendly interface.
H2O.ai	An open-source AI platform for ML.	90	Supports AutoML for automated model selection and tuning.
Weka	ML toolkit for data mining and predictive modeling based on java.	85	For building and evaluating ML models, a UI based.
KNIME	Data analytics platform with open source.	88	Visual programming for ML workflows.
IBM SPSS Modeler	Predictive analytics and data mining tool.	85	For building predictive models, the UI model is based.
Amazon SageMaker	ML service by AWS cloud	93	From data preparation to deployment, end-to-end ML-based.
Orange	Data visualization and ML tool with open-source.	85	For ML, it provides a visual programming interface.
IBM Cognos Analytics	With predictive analytics capabilities, a business intelligence tool	85	For risk prediction and reporting, it integrates with ML models.
Risk prediction using CNN and LSTM	Predicts the risk based on abnormal values possessed by significant factors.	98	SHAP, combining the outputs of CNN and LSTM.

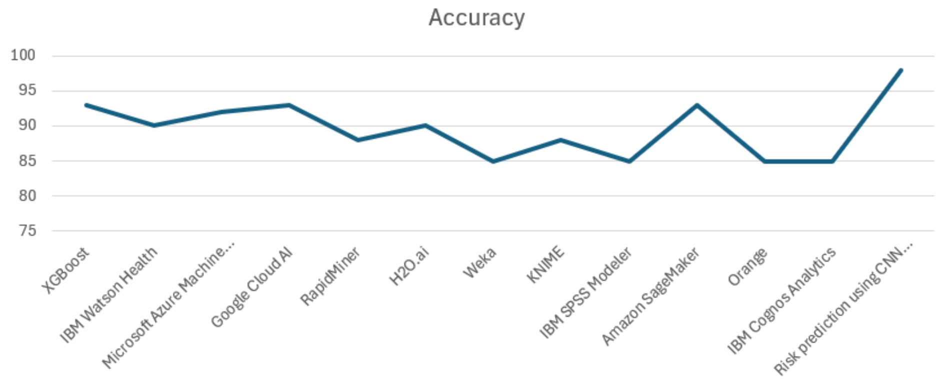

Fig. 6. Accuracies of the tools considered against our proposed model

From Table 10, specific market available tools are demonstrated with accuracies, along with their significant features. These tools against the hybrid model (CNN+LSTM) are compared and determined the accuracies. The accuracy of the proposed approach is best when compared against the other considered tools towards risk assessment.

Conclusion

The coronavirus has resulted in many people dying due to its unpredictable behavior, particularly its nature changes to severe in a few days. This behavior would cause many people who are not health conscious, not involved in rehabilitation, not consuming nutritious food, and older age. In this, the risk of coronavirus is severe or normal to be determined using a hybrid model that consists of CNN and LSTM, in which the former for spatial, and the latter is for temporal. The impact of post-COVID may affect any of the body's organs, such as the respiratory system, heart problems, muscle weakening, etc. The recommended practices to follow would help to recover from infection and return to a healthy normal or an improvement in health than the earlier stage. The significant recommendations proposed are AI-based monitoring, Effective rehabilitation and physical therapy, Digital and telemedicine, and AI mentor support, as well as real-time monitoring using wearable devices. In this, two aspects in which one is on organ damage and technology solutions to overcome from, and the second is severity classification using a hybrid model of CNN and LSTM.

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