**COVID 19 Mortality Prediction**

**An Engineering Project in Community Service**

**Phase – II Report**

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**Bonafide Certificate**

Certified that this project report titled “**Covid-19 Mortality Prediction**” is the bonafide work of “21BCY10210 Swati, 21BCY10014 Dhruv Sharma, 21BCY10123 Harshitaa Ashish, 21BCE10023 Shrey Patel, 21BCE10616 Chaudhary Mihirkumar, 21BCE11156 Meghavi Jadav, 21BCE11433 Shefali Jain, 21BAI10181 Vinamra Rawat, 21BSA10141 Aditiya Pandey” who carried out the project work under my supervision.

This project report (Phase II) is submitted for the Project Viva-Voce examination held on February 15, 2024.

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**ABSTRACT**

Early and accurate diagnosis of COVID-19 is essential for good patient care and reducing strain on healthcare systems. This paper proposes a smart algorithm to pick the best data points from a large set and build Machine Learning models to predict COVID-19. We then chose the model with the best performance.

Similar to our work, research has shown that Clinical Decision Support Systems (CDSS) can be helpful in diagnosing COVID-19. These systems assist doctors in making diagnoses by providing them with relevant information.

Our study looked at how computer programs can help doctors diagnose COVID-19. We searched major research databases and used data from there. We then tested different methods to find the best features for identifying COVID-19. The most accurate method was chosen for further development.

The studies used nonknowledge based CDSS and knowledge based CDSS. Convolutional Neural Networks (CNN) and Support Vector Machine (SVM) were employed to design the CDSS in most of the studies. Accuracy and sensitivity were the most common metrics for evaluating CDSS.

Many COVID-19 diagnosis helper programs (CDSS) use machine learning (ML) because of readily available chest scan data. While these ML-based CDSS show promise, they're new, and data quality can affect their reliability. More research is needed to compare different CDSS types and ensure they effectively assist doctors in diagnosing COVID-19.

**Keywords** - Clinical Decision Support Systems (CDSS), Machine learning, eHealth, Electronic Health Record (EHR), covid-19, Coronavirus, medical diagnosis, Telemedicine.

**1. INTRODUCTION**

The emergence of COVID-19 has presented a significant global health challenge. The unpredictable severity of the virus, ranging from asymptomatic to life-threatening, necessitates effective strategies for early detection and management. Rapid identification and isolation of infected individuals are crucial to curb the spread of the virus and lessen the burden on healthcare systems.

The rapid spread of COVID-19 has strained healthcare resources and overwhelmed providers. Efficient methods for prognosis and early detection are essential to optimise resource allocation and provide optimal patient care. Healthcare authorities require tools to assess patient conditions, prioritise cases, and manage limited resources effectively.

Developing intelligent diagnostic tools can significantly enhance COVID-19 detection and support timely intervention to minimise complications and mortality. These tools can leverage Artificial Intelligence (AI) techniques to reduce diagnostic errors and inter-rater variability in prediction, prognosis, and treatment decisions.

Diagnostic and prognostic models offer valuable insights for identifying high-risk patients and tailoring appropriate treatment plans. These models can reduce ambiguity by providing quantitative, objective, and evidence-based tools for risk stratification, prediction, and care planning. This translates to improved patient outcomes and survival rates by enabling clinicians to develop more effective strategies for managing complications.

Computational techniques, particularly Machine Learning (ML), have proven effective in disease classification and accurate diagnostic modelling. ML algorithms can extract valuable knowledge and patterns from large datasets, facilitating evidence-based decision-making in case identification, risk assessment, patient triage, and resource allocation.

Extensive research has explored the application of various ML algorithms for classifying and identifying COVID-19 cases. This study aimed to develop and evaluate different ML models for early COVID-19 detection, ultimately selecting the most effective model. This approach offers a practical solution for developing a diagnostic intelligence model that leverages clinical data to streamline COVID-19 screening procedures.

Early and precise diagnosis of COVID-19 is paramount for effective disease management and reducing the strain on healthcare systems. This study investigates the potential of Machine Learning to develop a diagnostic tool for early COVID-19 detection based on clinical data analysis. By leveraging the power of AI, we can create intelligent solutions to address the challenges posed by the COVID-19 pandemic and improve patient outcomes.

**1.1 Motivation**

Developing a machine learning model to predict mortality rates among COVID-19 patients is of paramount importance in the fight against the pandemic. By accurately identifying individuals at higher risk of adverse outcomes, such as severe illness or death, healthcare resources can be allocated more effectively, and timely interventions can be initiated to improve patient outcomes. This predictive model holds the potential to assist healthcare providers in making informed decisions regarding patient care, including treatment prioritisation and resource allocation. Furthermore, by understanding the factors contributing to COVID-19 mortality, such as comorbidities, demographics, and disease severity, we can tailor preventive measures and interventions to better protect vulnerable populations. Ultimately, the development of this model aims to enhance our ability to mitigate the impact of COVID-19, save lives, and contribute to the global efforts to control the spread of the virus.

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**1.2 Objective**

The primary objective of this project is to develop a machine learning model capable of accurately predicting mortality rates among COVID-19 patients. Specifically, our goals include:

Data Analysis: Conduct comprehensive analysis of COVID-19 patient data to identify key factors associated with mortality, including demographics, comorbidities, and disease progression indicators.

Model Development: Develop and train a robust machine learning model using advanced algorithms to predict mortality rates based on the identified factors.

Evaluation: Assess the performance of the developed model through rigorous evaluation techniques, including cross-validation and performance metrics such as accuracy, sensitivity, specificity, and area under the curve (AUC).

Interpretability: Ensure interpretability of the model results by providing insights into the relative importance of different predictors in determining mortality risk among COVID-19 patients.

**2. EXISTING WORK**

CovEWSis a clinical mortality risk prediction system for COVID-19 positive patients to be used in a continuous manner in both inpatient and outpatient settings. It uses clinical risk factors from a patient’s EHR to automatically calculate a mortality risk score between 0 and 100 that indicates the current risk percentile that this patient is in relative to the reference cohort. A CovEWS score of 90 indicates, for example, that the patient has a higher COVID-19 related mortality risk than 90% of COVID-19 positive patients in the reference cohort. CovEWS scores reflect the momentary risk of patients in their current states, and that they update instantaneously to reflect relevant, EHR-derived changes, which is a key differentiator of CovEWS compared to existing COVID-19 related mortality risk prediction systems that are not designed to take into account new, incoming clinical evidence. CovEWS maintains a high degree of interpretability for clinicians by indicating the relative positive and negative influences of each clinical risk factor over time on the predicted risk score. The information conveyed by CovEWS can be used to quickly and objectively assess individual COVID-19 related mortality risk in order to prevent or mitigate mortality, and optimise prioritisation of scarce healthcare resources.

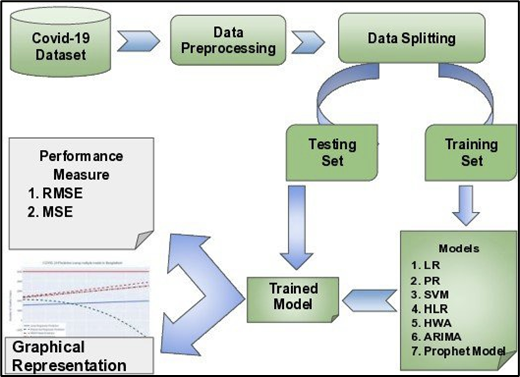
Further, Chintalapudi implemented the ARIMA model to predict the COVID-19 cases for the Italian ministry of health. The work attained an accuracy of 93.75 and 84.4% for COVID-19 cases and recovery cases respectively within February mid to end of March 2020. The model by authors in [19] achieved reduction of new cases enrollment by 35%.

A study in 2020 used a supervised XGBoost classifier as the predictor model. XGBoost is a high-performance machine learning algorithm that benefits from great interpretability potential due to its recursive tree-based decision system. In contrast, internal model mechanisms of black-box modelling strategies are typically difficult to interpret. The importance of each individual feature in XGBoost is determined by its accumulated use in each decision step in trees. This computes a metric characterising the relative importance of each feature, which is particularly valuable to estimate features that are the most discriminative of model outcomes, especially when they are related to meaningful clinical parameters.

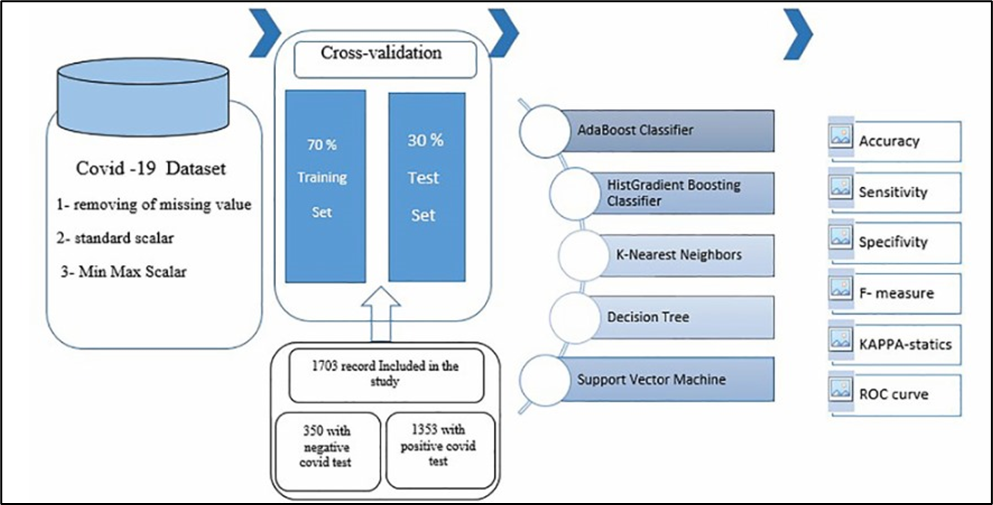
Analysis of CT scans and Chest X-ray images were approached for the classification of COVID-19 infection in the lungs. A study was conducted to classify COVID-19 using lung CT scan images. GLCM (Gray-Level Co-occurrence Matrix) has been proposed to calculate features for ELM (Extreme Learning Machine), a single hidden layer neural network algorithm. The evaluation of this approach was done using K-F cross-validation with ten-fold cross-validation.

**3. TOPIC OF THE WORK**

**a) System Design / Architecture**

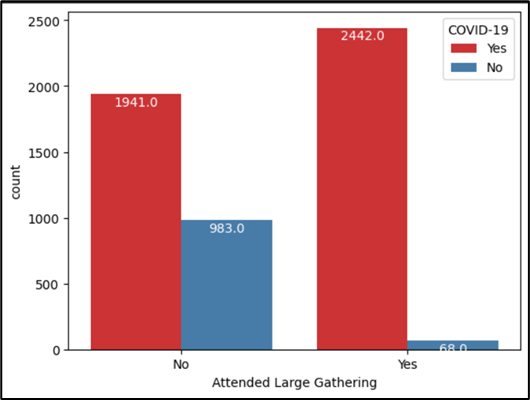


**b) Working Principle**



**c) Results and Discussion**

In this study, we processed a large dataset of COVID-19 confirmed cases collected from all around the world, and used state of the art machine learning algorithms to predict the mortality rate for patients with COVID-19. We evaluated the developed algorithms using several different metrics. The evaluation results demonstrate high accuracy and the effectiveness of the developed models.



**d) Individual Contribution by members**

**Swati-21BCY10210**

Scoured diverse databases to procure the ideal dataset, ensuring its relevance and reliability for our analysis. Then, I applied my visualisation skills to craft insightful graphs and charts, rendering complex data comprehensible and engaging. Additionally, I undertook the crucial task of preprocessing the dataset, meticulously cleaning and formatting it to ensure accuracy in our analyses. Lastly, I dedicated time to reviewing pertinent research papers, extracting valuable insights to inform our project's direction. My holistic contributions were pivotal in shaping our project's success. Being the group leader, sincerely managed the team communication with faculties as well as team members.

**Shrey Patel- 21BCE10023**

​​My personal involvement in both the documentation and review article concerning the predictive model for COVID-19 mortality using machine learning encompasses several pivotal aspects. Within the documentation section, my responsibility lied in crafting a clear and insightful introduction that places our model's significance within the wider context of the COVID-19 crisis.

Furthermore, my role involved outlining the datasets utilized to train and validate our mortality prediction model, elucidating their sources, characteristics, and any preprocessing steps taken. Additionally, I elaborated on the framework of our machine learning model, explaining the specific algorithms and approaches employed for forecasting COVID-19 mortality.

Concurrently, I was tasked with delineating the evaluation metrics employed to assess the performance of our model and presenting the obtained results, along with their interpretation, to ensure a comprehensive understanding of our findings.

Transitioning to the review paper, my role involves conducting an extensive literature review on existing mortality prediction models for COVID-19. This review will cover methodologies, datasets, characteristics, machine learning techniques, evaluation criteria, and model effectiveness. Based on these insights, I will carefully analyse the strengths and weaknesses of current models, pinpointing gaps in the literature and suggesting potential areas for enhancement.

Subsequently, I entailed the broader significance of mortality prediction models for COVID-19 and proposing strategies for future research endeavours and collaborations.

**Dhruv Sharma 21BCY10014**

Spearheaded the quest for the ideal dataset, meticulously scouring numerous sources to pinpoint one that aligned perfectly with our objectives. Leveraging my analytical skills, I deftly visualised the dataset, transforming raw information into compelling graphics that illuminated key insights. Additionally, I undertook the crucial task of preprocessing the data, ensuring its integrity and suitability for analysis. Moreover, I reviewed an extensive amount of research papers, extracting valuable insights to inform our approach. My comprehensive efforts were instrumental in shaping the project's trajectory and eventual outcomes.

**Chaudhary Mihir Kumar 21BCE10616**

My individual contribution to the documentation and review paper on the mortality prediction model for COVID-19 using machine learning involves several key aspects. In the documentation section, I am responsible for providing a clear and insightful introduction that contextualises the significance of our model within the broader landscape of the COVID-19 pandemic.

Transitioning to the review paper, I undertook a thorough literature review focusing on existing mortality prediction models for COVID-19. This review encompassed methodologies, datasets, features, machine learning algorithms, evaluation metrics, and model performance. Drawing from these findings, I critically analysed the strengths and limitations of current models, identifying gaps in the literature and opportunities for improvement. Subsequently, I led the discussion section, synthesising key insights from the literature review and offering critical perspectives on the implications for clinical practice and research. This involved addressing the broader significance of mortality prediction models for COVID-19 and proposing strategies for future research and collaboration. Ultimately, in the conclusion section, I summarise the main findings of the review paper, highlighting its contributions to advancing our understanding of mortality prediction for COVID-19 using machine learning and proposing directions for future research and application. Through these efforts, I contributed to the advancement of knowledge and informed decision making in predicting mortality rates in COVID-19.

**Harshitaa Ashish**

In our group project, I took on a diverse set of responsibilities, each crucial to our success. Initially, I delved into extensive research to identify and procure the most suitable dataset, ensuring its relevance and reliability. Subsequently, I applied my expertise in data visualization to craft visually compelling representations of the dataset, facilitating clearer interpretation and understanding of complex patterns and insights. Moreover, I meticulously preprocessed the data, employing various techniques to clean, normalize, and prepare it for analysis, ensuring its integrity and usability. Additionally, I undertook the task of reviewing pertinent research papers, synthesising valuable insights to inform our project's approach and methodology. Furthermore, I leveraged my knowledge in machine learning to implement advanced algorithms and models, enriching our analysis and driving innovation in our project. My comprehensive contributions across these domains were integral to our project's success, demonstrating versatility and proficiency in diverse aspects of data science and machine learning.

**21BCE11156 Meghavi Jadav**

In our group project focused on predicting COVID-19 mortality rates, I spearheaded the machine learning component. Using Python and relevant libraries, I developed sophisticated algorithms and models aimed at accurately forecasting mortality rates. Through meticulous coding and iterative refinement, I ensured the robustness and precision of our predictive models. Collaborating closely with team members, I integrated our machine learning predictions seamlessly into the project framework. My dedication to coding and machine learning methodologies significantly bolstered our project's predictive capabilities, playing a pivotal role in addressing the challenges posed by the COVID-19 pandemic with data-driven insights.

**21BCE11433 Shefali Jain**

In our group project focused on predicting COVID-19 mortality rates, I spearheaded the development of the machine learning component. I engineered predictive models tailored to forecast mortality rates accurately. I meticulously fine-tuned algorithms, integrating diverse data inputs such as demographics and infection rates to enhance model. Collaborating closely with team members, I ensured seamless integration of our machine learning predictions into the project framework. My dedication to coding and machine learning methodologies played a pivotal role in enhancing the predictive capabilities of our project, contributing significantly to addressing COVID-19 challenges.

**21BAI10181 Vinamra Rawat**

In our collaborative project targeting COVID-19 mortality rates, I led the development of predictive models through coding. My role involved extensive Python scripting to craft robust algorithms tailored for mortality rate prediction. Employing machine learning techniques, I meticulously trained and fine-tuned these models using relevant datasets. Through rigorous testing and validation, I ensured the accuracy and reliability of our predictions. Moreover, I collaborated closely with team members to seamlessly integrate the predictive code into our project framework. My dedicated focus on coding and predictive modeling significantly bolstered the project's capacity to forecast COVID-19 mortality rates accurately, enhancing its overall impact and efficacy.

**5. CONCLUSION**

Doctors are increasingly using computer programs to help them diagnose diseases like COVID-19. These programs are called Clinical Decision Support Systems (CDSS) and they can be based on either established medical knowledge or use cutting-edge tech like machine learning (ML). This study looked at how well these CDSS systems work.

The researchers found that both knowledge-based and ML-based CDSS could help diagnose COVID-19. ML was the most common technique used, likely because there's a lot of data available from chest X-rays and CT scans of COVID patients. However, there are concerns that this data might be biased and the accuracy of these systems needs more real-world testing.

Overall, these CDSS systems have promise but need more development. Future studies should test them in different hospitals and clinics, and see if they can be used throughout a patient's COVID care, from prevention to recovery. This research can help doctors, policymakers, and anyone working on fighting the pandemic.

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| **Technical Skills**  **Certification** | **HTML, CSS , Javascript, Angular js, Mongo db, SQL, Node.js, Express.js, Java, Python**  **IBM AI Engineering** |

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| **Dhruv Sharma** | **Registration Number: 21BCY10014**  **Email:dhruv.sharma2021**[**@vitbhopal.ac.in**](mailto:swati2021@vitbhopal.ac.in)  **Phone: 7058156758**  **LinkedIn:** [**https://www.linkedin.com/in/dhruv-sharma-bb1a65223/**](https://www.linkedin.com/in/dhruv-sharma-bb1a65223/) |
| **Technical Skills** | **Web-Dev front end, Python, Data visualisation** |

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| **Technical Skills Certification** | **CEH-Certified Ethical Hacker, Computer Networking, AWS- Certified Cloud Practitioner** |

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| **Technical Skills Certification** | **Python, IT Networking, Ethical Hacking(CEH), Machine learning** |

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| **Technical Skills Certification** |  |

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| **Technical Skills Certification** |  |

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| **Shefali Jain** | **Registration Number: 21BCE11433**  **Email:** [**shefali.jain2021@vitbhopal.ac.in**](mailto:shefali.jain2021@vitbhopal.ac.in)  **Phone: +91 88188 52535**  **LinkedIn:** [**https://www.linkedin.com/in/shefali-jain-2a8157221/**](https://www.linkedin.com/in/shefali-jain-2a8157221/) |
| **Technical Skills Certification** | **Frontend Developer, MongoDB, AWS- Certified Cloud Practitioner, IBM AI Engineering, Java** |