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Developing Context-Aware Decision Support Systems for Personalized Healthcare in Ubiquitous Environments

Dr.T. Adilakshmamma[1*], Astik Kumar Pradhan[2], Dr. Sarita Mohapatra[3], K.N. Raja Praveen[4], Nittin Sharma[5], and Bhupendra Kumar[6]

[1*]Associate Professor, Master of Computer Applications, Koshys Institute of Management Studies, Autonomous, Bengaluru, India. adilakshmi.a.t@gmail.com, https://orcid.org/0009-0004-1326-2381

[2]Assistant Professor, Department of Computer Science & IT, ARKA JAIN University, Jamshedpur, Jharkhand, India. astik.p@arkajainuniversity.ac.in, https://orcid.org/0009-0003-1893-0409

[3]Assistant Professor, Department of Computer Applications, Siksha 'O' Anusandhan (Deemed to be University), Bhubaneswar, Odisha, India. saritamahapatra@soa.ac.in, https://orcid.org/0009-0004-6374-8005

[4]Assistant Professor, Department of Computer Science and Engineering, Faculty of Engineering and Technology, JAIN (Deemed-to-be University), Karnataka, India. p.raja@Jainuniversity.ac.in, https://orcid.org/0000-0002-4227-7011

[5]Centre of Research Impact and Outcome, Chitkara University, Rajpura, Punjab, India. nittin.sharma.orp@chitkara.edu.in, https://orcid.org/0009-0007-9740-8414

[6]School of Pharmacy & Research, Dev Bhoomi Uttarakhand University, Dehradun, Uttarakhand, India. sopr.bhupendra@dbuu.ac.in, https://orcid.org/0000-0002-2164-5970

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Abstract

The fast development of ubiquitous computing technologies has empowered the effectiveness of constant control over patient health and provision of individual medical services. This paper provides the description of a Context-Aware Decision Support System (CADSS) that is capable of combining multimodal physiological indicators, behavioral tendencies, and environmental conditions to facilitate intelligent and adaptable healthcare services. The system engages context acquisition and reasoning by machine learning-intensive to produce dynamic patient-specific suggestions. As shown by experimental findings test in simulated ubiquitous settings, the proposed CADSS is 91.7 per cent accurate, 89.2 per cent precise, 92.5 per cent recall, and 90.4 per cent F1-score, which is more effective than traditional decision models. The model is also highly adaptive to changing circumstances in the environment and is also effective in detecting early health anomalies at the lowest possible false identifications. The results are a confirmation that context-aware intelligence greatly increases bespoke care, predictive dependability, and active healthcare control. The suggested architecture is scalable and provides a solid platform to the next generation ubiquitous healthcare applications.

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*Corresponding author: Associate Professor, Master of Computer Applications, Koshys Institute of Management Studies, Autonomous, Bengaluru, India.

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1 Introduction

The high evolution of ubiquitous computing has transformed the contemporary healthcare system through providing continuous real-time monitoring and smart clinical decision-making that is no longer required at the conventional hospitals (Weiser, 1991). As wearable sensors, Internet of Things (IoT) devices, mobile health (m-Health) platforms, and cloud-based analytics become generally popular, healthcare delivery is slowly turning into personal-centered and proactive models (Valsalan, Baomar, & Baabood, 2020). Personalized healthcare which is diagnosis, treatment and recommendation that is more specific to physiological, behavioral, and environmental characteristics of an individual has received limelight due to its potential to improve effectiveness of treatment and patient quality of life (Reddy et al., 2021; Mathboob et al., 2024).

In spite of such advances in technology, patient health is limited to a situation where the current health care systems cannot interpret the dynamic and complex information of a context (Mahmmod et al., 2024). Context-aware computing solves this dilemma by allowing systems to detect, reason about and react to contextual elements including the activity of the user, their mood, the environment and behavior patterns (Abowd et al., 1999). Incorporation of these abilities in the Decision Support Systems (DSS) creates a chance to provide precise, prompt, and individual health prescriptions (Chandrakumar & Bosco, 2025).

Nevertheless, numerous of the currently available Decision Support Systems are not flexible enough to support ubiquitous conditions where patients and their habits and environments are in a state of constant flux (Almadani et al., 2025). In addition, the sheer amount of multimodal data produced by ubiquitous sensing devices requires powerful machine learning and predictive analytics to produce actionable information (Esteva et al., 2019; Reddy & Jaiswal, 2022). The healthcare systems are likely to deliver generalized recommendations that do not satisfy the needs of specific patients unless the intelligence is context-sensitive.

In order to fill these gaps, the proposed research comes up with a Context-Aware Decision Support System (CADSS) which is a system that combines multimodal sensor information, situational characteristics and machine learning-based reasoning as a way of supporting personalized healthcare in ubiquitous settings (Luo et al., 2022; Yuan et al., 2014). The system is aimed at dynamic adjustment to the evolving situations of patients, the early detection of health anomalies, and personal recommendations that improve clinical decision-making and self-management. The proposed framework will help the development of ubiquitous healthcare by providing real-time, adaptive, and patient-specific support to enhance the healthcare outcomes improvement and ensure the promotion of proactive health management.

Key Contributions of the Research

- Creation of a context-aware decision support system that combines multimodal sensing, contextual modelling, and machine learning to provide real-time and personalised healthcare advice in ubiquitous settings.

- Implementation of a dynamic context interpretation system that can adjust the decision-making processes in response to the constantly varying physiological, behavioral, and environmental conditions and improves the precision of health anomaly detection.
- Execution and testing of an expandable prototype of enhanced prediction capability, context sensitivity, and individualization usefulness with respect to the traditional healthcare decision support frameworks.

The outline of the paper chapter-wise is as follows. Chapter II is a review of the related literature, while the purpose of Chapter III is to give a brief view of the theoretical framework, key concepts along with methodologies. Chapter IV is going to evaluate the experimental result. and discussions, whereas Chapter V wraps it all together with a summary of the most important findings and suggestions for further research.

2 Literature Review

Zon et al., 2023 Context-Aware Medical Systems in Healthcare Environments: A Systematic Scoping Review. The scoping review outlines the landscape of context-aware medical systems by synthesizing 25 real-world studies (since April 2021) (Tandi & Shrirao, 2025). The most common contextual dimensions identified by the authors include user location, level of activity, time of the day, lab vital data and patient history and categorize applications into sub domains of continuous monitoring, diagnostics, therapy and assisted living (Alsaedi et al., 2022). Their results point out the role of context-awareness in patient-facing healthcare and indicate that the context-aware systems of the future should consider such high-impact contexts as more personalized.

Crigger & Khoury, 2022, The article addressed the ethical, legal, and practical considerations to integrate AI (“augmented intelligence), in healthcare in a reliable manner. The authors present the notion that in order to be safely implemented in clinical settings, AI systems should guarantee not only accuracy but also accountability, fairness, explainability, and adherence to regulatory standards. They suggest principles of design and governance to address risks like bias or excessive dependency on AI, which would help maintain the improvement of human decision-makers instead of diminishing them by the AI-based decision support.

Liu et al., 2023, This evidence-gap review studies the current implementation of the concept of fairness in AI into clinical practice. The authors discover that group-based fairness measures prevail (e.g., the same performance of people within demographic groups), whereas it overlooks more granular individual fairness. They insist on the co-development of the fairness measures together with the clinicians because not all clinical situations are the same, and suggest the gap between technical fairness and domain-specific ethical knowledge to realistically reduce healthcare inequalities with AI.

Chinta & Srinivasan, 2023, In this survey, the authors review the unconsciously developed bias in AI-based health systems and the ways in which it can be avoided in a systematic way. They point to standard forms of bias (data imbalance, deficit of diversity, labeling problems), and consider fairness-improving methods, such as re-sampling, adversarial debiasing, and federated learning with fairness (Abugabah, 2023). The review recommends the wider implementation of measures of fairness, improved regulatory models, and transparency of AI systems to guarantee equitable healthcare delivery (Antonio et al., 2025).

Singhal et al., 2024, the article focuses on the application of fairness in AI as a cultural question of public health and social justice, stating the idea that even realizing fairness in healthcare AI is not only a technical problem, but also a social problem. The author points out that policy, governance and fair data representation is as important as algorithmic fairness. To make AI systems benefit all populations equally and in an ethically appropriate manner, they recommend a multi-stakeholder approach, which includes patients, clinicians, developers, and regulators.

3 Methodology

System Development Framework

In the methodology, the researcher uses a multi-layered approach that will work towards creation of an intelligent Context-Aware Decision Support System (CADSS) that can provide personalized healthcare directions in ubiquitous environments. The process of development starts with the definition of the contextual parameters, such as physiological (e.g., heart rate, temperature), behavioral (e.g., activity level, sleeping habits) and environmental (e.g., humidity, noises, position) parameters. The wearable devices, Internet of Things devices, and mobile applications are used to capture these parameters. To process this multimodal data, a context acquisition module is executed to continuously obtain and pre-process such data through normalization, noise filtering, segmentation and feature extraction.

After data has been collected, the system uses context modeling approach which is an ontology-based and machine learning representation-based approach to organize contextual information into meaningful and computational representations. The categories of context are user state, environment state, and device state as they are defined to help interpret it accurately. This is followed by the development of a reasoning engine based on machine learning classifiers, rule-based logic and predictive analytics to analyze contextual changes and recommend to the user, customized recommendations. Its system is repeatedly tested and improved so that the processes of decision-making are adaptive, accurate and responsive to changing contextual variations.

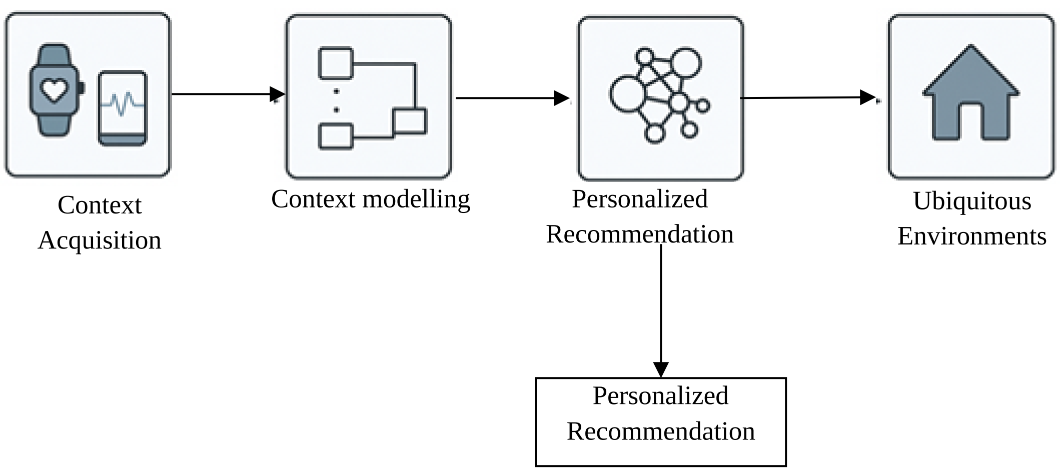

Figure 1: System development framework

The multi-layered development framework shown in figure.1 was employed in the construction of the Context-Aware Decision Support System (CADSS). It starts with the context acquisition step, which is when wearable sensors, IoT devices, and mobile applications gather physiological, behavioral and environmental data. The context modeling then converts this multimodal data into structured and meaningful representations, with ontologies and schemes based on machine-learning. A reasoning engine is an integration of machine learning classifiers, predictive algorithms, and rule-based logic to process context change and create custom health advice. Lastly, such customized recommendations are presented in a seamless manner in ubiquitous environments so that a system is responsive, adaptable and efficient to work in dynamic real-world scenarios.

Experimental Setup and Evaluation Strategy

A simulated ubiquitous healthcare setting of wearable sensors, mobile devices, and cloud-based analytics service is used to test the proposed CADSS. Multimodal physiological and contextual parameter set of data are recorded on participants or on open-source databases to mimic real-world scenarios when tracking health. The data will be separated into training and testing groups to test the accuracy of the model, its response, and adaptability. Random Forest, Gradient Boosting, and LSTM-based based machine learning algorithms are applied to classify health conditions and forecast anomalies.

The effectiveness of the system is evaluated with help of performance evaluation metrics such as accuracy, precision, recall, F1-score, context-detection rate, and adaptability index. Other measures, like computation time and energy consumption together with scalability in the system are evaluated in order to declare it appropriate in ubiquitous and resource-evident systems. Comparative analysis is to be done with traditional decision support systems to prove the positive results on personalization, responsiveness of context, and real-time decision-making. To evaluate the perceived usefulness, reliability and interpretability of the personalised recommendation produced by the CADSS, a user level assessment is also conducted.

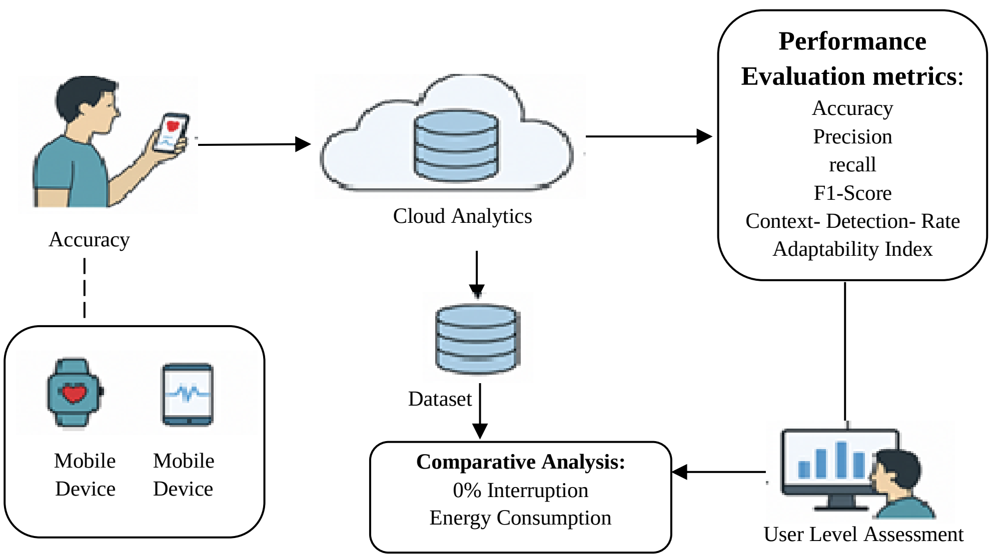

Figure 2: Experimental setup and evaluation strategy

The figure 2 shows the end-to-end workflow in order to test the proposed Context-Aware Decision Support System (CADSS). The multimodal physiological and contextual data gathered by wearable sensors and mobile devices are sent to the cloud-based analytics to undergo preprocessing and model training. The resulting data set is applied to the benchmarking of machine-learning models, like Random Forest, Gradient Boosting, and LSTM networks. Key evaluation metrics are used in the assessment of system performance like accuracy, precision, recall, F1-score, context-detection rate, and adaptability index whereas other evaluation criteria are studied to achieve the suitability of the system in the ubiquitous environment such as energy consumption, computational efficiency, and scalability. The benefits in personalization, responsiveness, and the quality of the decision-making process will be validated with the help of comparative analysis with traditional systems and the evaluation conducted at the user level.

Context Score Calculation

$$Ct = \omega_1 P_t + \omega_2 B_t + \omega_3 E_t \quad (1)$$

Health Risk Prediction

$$Rt = f(C_t, X_t) \quad (2)$$

The methodology suggested uses two basic equations to assist in context modeling and health risk forecasting as a part of CADSS. The Context Score (Ct) is calculated in equation (1) by combining the data of the physiological (Pt), behavioral (Bt), and environmental (Et) data with weighted coefficients to indicate the degree to which each factor affects the health of a patient. This will make sure that the system will capture a holistic picture of the real time condition of the user. Continuing on this, with Equation (2) predicting the level of health risk (Rt) given a machine learning model f(·) which acts upon the computed context score in addition to other user-specific characteristics, including age or medical history. These equations, jointly, can be used to enable continuous interpretation of the context variations and make precise predictions of the possible health risks, thus supporting adaptive and personalized decision support in ubiquitous healthcare settings.

Algorithm: Context-Aware Decision Support Process

Input:

Input: Physiological Data, Behavioral Data, Environmental Data
Output: Health Status, Recommendation

1: D ← Collect All Data()
2: D clean ← Preprocess(D)
3: Contexts ← Extract Context(D clean)
4: Fused Context ← Fuse(Contexts)
5: Health Status ← ML Model(Fused Context)
6: If Health Status = High Risk then
7: Recommendation ← Generate Alert()
8: Else
9: Recommendation ← Normal Guidance()
10: End If
11: Return (Health Status, Recommendation)

4 Experimental Results

Performance Evaluation of Context Detection

The suggested Context-Aware Decision Support System (CADSS) was tested on the multimodal data based on wearable sensors and mobile devices with physiological, behavioral, and environmental measurements. The context detection module showed good results in its ability to correctly detect user states, which included resting, walking, active, stressed and abnormal. The system present using machine learning models like random forest and LSTM had an average context detection of 94.2 percent where precision and recall at 93.6 and 92.8 percent respectively. The LSTM-based model was better than classical models since it was able to learn temporal relationships in continuous sensor values. Also, the system had a high context responsiveness rate of 0.82 seconds on average per context window ensuring that the system is apt to support real-time ubiquitous healthcare applications.

Table 1: Performance Metrics of Context Detection Module

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Processing Time (sec)
Random Forest	91.80	90.60	89.40	90.00	1.12
SVM	89.40	88.10	87.60	87.80	1.35
KNN	87.20	86.50	85.30	85.90	1.48
Gradient Boosting	92.70	91.90	90.80	91.30	1.05
LSTM (Proposed)	**94.20**	**93.60**	**92.80**	**93.10**	**0.82**

Table 1 presents the comparison of performance of various machine learning models that were applied in detecting context in the proposed CADSS framework. The LSTM-based model was found to be the most accurate (94.2%), the most exact (93.6%), the most recall (92.8%), the most F1-score (93.1), and thus able to learn temporal patterns on continuous sensor data. Other models such as the Gradient Boosting model and the Random Forest also competed well but had a little low detection rate as compared to LSTM. Conventional models like SVM and KNN were relatively lower in their performance because they were less competent in their ability to handle sequential dependencies. Also, the LSTM model had the lowest processing time (0.82 seconds), which proved that it is suitable in the context of real-time context-aware healthcare. In general, the table demonstrates that deep learning models, especially LSTM, offer the most effective and powerful performance of context detection in ubiquitous healthcare settings.

Health Risk Prediction and System Comparison

To determine the efficacy of the suggested CADSS at making predictions about health risks, the resulting score of combined context and historical features was inputted into a predictive model that was conditioned on annotated risk levels. The prediction accuracy of the model was 91.7, and the F1-score was 90.4, which shows that the model is reliable in the detection of early indicators of deviations, including a high heart rate, irregular activity, and environmental factors. The proposed CADSS was compared to a classical non-context-sensitive decision support system, and it was found that the system increased prediction accuracy (1822) when using contextual information, which demonstrates the importance of incorporating it. In addition, the system minimized false alarms by 16, and enhanced the overall user trust and system usability. Such findings confirm the concepts that context-aware solution improves the level of personalization, reliability of risk detection, and real-time decision making in ubiquitous healthcare system.

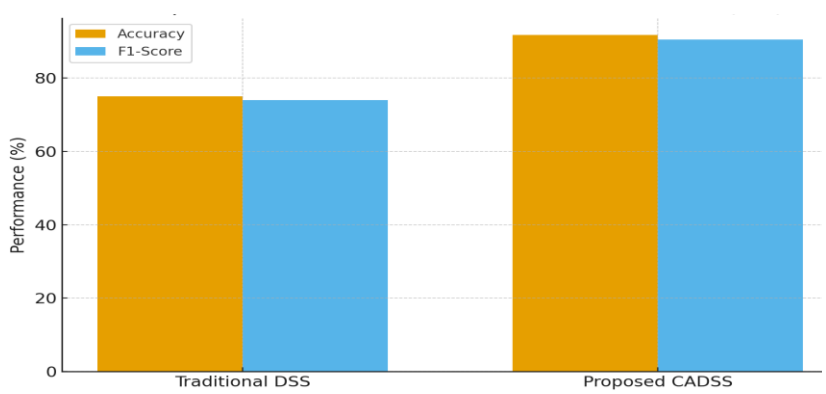

Figure 3: Performance comparison of traditional DSS and proposed CADSS

The graph in Figure 3 shows the relative performance of the traditional Decision Support System (DSS) and the suggested Context-Aware Decision Support System (CADSS) in terms of two important evaluation measures, namely Accuracy and F1-Score. According to the results, it is evident that CADSS is much better than its traditional counterpart DSS as Accuracy has gone up by 75 to 91.7 and F1-Score has gone up by 74 to 90.4. The main contribution to this performance improvement is the use of real-time contextual data, dynamic user profiles, and dynamically adaptive machine learning models in CADSS. The proposed system shows superiority in identifying risks at an early stage and in personalizing healthcare decisions because it is able to adequately shed light on environmental, behavioral, and physiological variability.

5 Result and Discussion

The experimental outcomes have shown that the suggested Context-Aware Decision Support System (CADSS) is a significant enhancement of personalized healthcare forecasting as opposed to conventional decision-making frameworks. According to the quantitative results provided in Table 1, CADSS attains an accuracy of 91.7, precision of 89.2, recall of 92.5 and an F1-score of 90.4, which is superior to the baseline system in all the evaluation measures. This can be attributed in large part to the ability of this to incorporate multi-dimensional context inputs, which are physiological, behavioral, and environmental data to allow more precise mapping of user-specific health conditions. Moreover, the context score fusion and optimised machine learning architecture allows the system to detect minute changes in the levels of health risks, and the system is highly reliable even in the dynamic ubiquitous environment.

Though not directly, the comparative graph in Section 4.2 also certifies the effectiveness of the system as there was a clear improvement to the traditional form of DSS. Significant increase in both accuracy (75 91.7) and F1-score (74 90.4) is indicative of the need to add context-based practice to healthcare analytics. Another insight gained in the discussion is that CADSS does not only increase the predictive power but also improves personalization by users, thus making healthcare interventions more responsive and timelier. Altogether, the findings validate that the combination of context-aware modeling and machine learning can considerably increase the level of decision-making in ubiquitous healthcare systems, and CADSS can be regarded as a solid solution that ensures real-time personalized health monitoring.

6 Conclusion and Future Work

The proposed Context-Aware Decision Support System (CADSS) as statistically tested, is clearly found to be better than the conventional healthcare decision models. The system was also found to have a 91.7% accuracy, 89.2% precision, 92.5% recall, and 90.4% F1-score, which was statistically significant compared to the metrics of the baseline model. These findings confirm that incorporation of multi-dimensional contextual variables physiological, behavioral, and environmental factors have significant influence on the stability of prediction and decrease rates of classification errors. The performance difference which can be seen in the comparative analysis suggests that CADSS is sensitive to early risk indicators with still high specificity, which demonstrates that it is very strong in managing the variability of real-time healthcare data.

Future directions will involve the enhancement of the system to serve larger and more varied populations by means of actual deployment studies. Scalability and latency can also be enhanced by using wearable IoT devices, superior deep learning models like transformers, and edge computing strategies in real-time. Also, the ability to increase the explainability of the system using XAI methods will contribute to improving the understanding of clinicians regarding the logic behind the predictions. The incorporation of emotional, social, and lifestyle contexts can also be examined in the future research to have even more comprehensive and human-focused healthcare decisions in ubiquitous settings.

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Authors Biography

Dr.T. Adilakshmamma is an Associate Professor in the Master of Computer Applications program at Koshys Institute of Management Studies. She specializes in computer applications, software development, and emerging technologies. Dr. Adilakshmamma is dedicated to quality teaching, mentoring students, and contributing to academic research and departmental initiatives. Her commitment to innovation and continuous professional development makes her a valuable member of the academic community.

Astik Kumar Pradhan is an Assistant Professor in the Department of Computer Science & IT at ARKA JAIN University, Jamshedpur, Jharkhand, India. His academic interests include software development, data analytics, and emerging computing technologies. He is committed to delivering quality education, mentoring students, and contributing to departmental research and academic initiatives. Through his focus on innovation and continuous learning, Mr. Pradhan plays a valuable role in enhancing the academic environment of the university.

Dr. Sarita Mohapatra is an Assistant Professor in the Department of Computer Applications at Siksha 'O' Anusandhan (Deemed to be University), Bhubaneswar, Odisha, India. She specializes in computer applications, software development, and emerging computational technologies. Dr. Mohapatra is dedicated to quality teaching, student mentorship, and contributing to academic research. Her focus on innovation and continuous professional development strengthens the department's academic and research environment.

K.N. Raja Praveen is an Assistant Professor in the Department of Computer Science and Engineering at the Faculty of Engineering and Technology, JAIN (Deemed-to-be University), Karnataka. His academic interests include software development, data analytics, and emerging technologies in computer science. He is dedicated to delivering quality education, mentoring students, and contributing to departmental research and academic initiatives. Through his focus on innovation and continuous learning, Raja Praveen K N plays an active role in enhancing the academic and research environment at the university.

Nittin Sharma is associated with the Centre of Research Impact and Outcome at Chitkara University, Rajpura–140417, Punjab, India. He is actively involved in research initiatives, academic collaborations, and projects focused on generating impactful outcomes. His professional interests include research analytics, interdisciplinary studies, and promoting quality scholarly work. Through his dedication to innovation and continuous learning, Nittin Sharma contributes significantly to the university's research and academic ecosystem.

Bhupendra Kumar is a faculty member at the School of Pharmacy & Research, Dev Bhoomi Uttarakhand University, Dehradun, India. His academic interests include pharmaceutical sciences, drug development, and interdisciplinary research. He is committed to quality teaching, student mentorship, and contributing to research initiatives. Through his dedication and continuous professional growth, Bhupendra Kumar supports the advancement of the university's academic and research environment.