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Smart Multimodal Neonatal Screening System Using Salivary Biomarkers

A. Naveen[1], N. Shahul Hameed[2], R. Thilagar[3], S. Vishwabharathi[4], Dr. S. Sutha[5]
[1,2,3,4]Student, Department of Biomedical Engineering, Dhanalakshmi Srinivasan Engineering College (Autonomous), Perambalur, Tamil Nadu, India
[5]Professor, Department of Biomedical Engineering, Dhanalakshmi Srinivasan Engineering College (Autonomous), Perambalur, Tamil Nadu, India

Abstract: Neonatal healthcare is a critical domain in modern medicine, focusing on the survival, growth, and development of newborn infants during the first few weeks of life. Early detection of neonatal disorders such as jaundice, dehydration, and neurological abnormalities plays a vital role in preventing long-term complications and reducing infant mortality rates. However, conventional diagnostic techniques primarily rely on blood-based tests, which are invasive, time-consuming, and often require well-equipped laboratory facilities and trained personnel. These limitations make such methods less suitable for continuous monitoring and challenging to implement in rural or low-resource settings. In recent years, there has been growing interest in the development of non-invasive diagnostic approaches that can provide accurate and real-time health assessment without causing discomfort to the patient. Among various biological fluids, saliva has emerged as a promising diagnostic medium due to its ease of collection, safety, and ability to reflect physiological and biochemical conditions of the body. Saliva contains a wide range of biomarkers, including enzymes, proteins, hormones, and metabolites, which can be used to detect various health conditions. The non-invasive nature of saliva collection is particularly beneficial for neonatal applications, where minimizing pain and stress is of utmost importance. The proposed system introduces a smart multimodal neonatal screening approach that utilizes salivary biomarkers for disease detection. By integrating microfluidic technology, optical sensing, and artificial intelligence, the system aims to provide a comprehensive and efficient diagnostic solution. Microfluidic chips enable precise handling of small sample volumes and facilitate controlled biochemical reactions, while optical sensors detect colour changes corresponding to biomarker concentrations. These signals are processed using embedded systems and analysed using machine learning algorithms to classify neonatal conditions accurately. Furthermore, the incorporation of smartphone-based imaging and mobile applications enhances the accessibility and usability of the system. The ability to store and transmit data through cloud platforms enables remote monitoring and telemedicine applications, making the system highly suitable for deployment in rural and underserved areas. Overall, the proposed system represents a significant advancement in neonatal healthcare by combining non-invasive diagnostics with modern technological innovations.

Keywords- Neonatal Screening, Salivary Biomarkers, Neonatal Jaundice, Dehydration Detection, Neurological Risk, Non-Invasive Diagnostics, Biosensors, Smart Healthcare Systems

I. INTRODUCTION

Neonatal healthcare is a critical domain in modern medicine that focuses on the survival, growth, and development of newborn infants during the first few weeks of life. This period is highly sensitive, as neonates are vulnerable to a wide range of health complications such as jaundice, dehydration, infections, and neurological disorders. Early detection and timely intervention are essential to prevent severe complications and reduce infant mortality rates. However, conventional diagnostic techniques primarily rely on blood-based testing, which is invasive, painful, and often requires well-equipped laboratory facilities along with skilled personnel.

These limitations make such methods less suitable for continuous monitoring and challenging to implement in rural and low-resource settings. In recent years, there has been increasing interest in developing non-invasive diagnostic methods that can provide accurate and real-time health assessment without causing discomfort to patients. Among various biological fluids, saliva has emerged as a promising diagnostic medium due to its ease of collection, safety, and ability to reflect the physiological and biochemical state of the body. Saliva contains a variety of biomarkers, including proteins, enzymes, hormones, and metabolites, which can be used to detect different health conditions.

The non-invasive nature of saliva collection is particularly advantageous for neonatal applications, where minimizing stress and risk is of utmost importance. Advancements in biomedical engineering have enabled the integration of multiple technologies to develop smart diagnostic systems. Microfluidic technology, also known as lab-on-a-chip, allows precise handling of small volumes of biological samples and facilitates rapid biochemical reactions. These systems are compact, cost-effective, and suitable for point-of-care applications. Optical sensing techniques are widely used to detect colour changes resulting from biochemical reactions, providing a simple and efficient method for analysing biomarker concentrations.

The combination of microfluidics and optical sensing forms the foundation for developing portable and accurate diagnostic devices. Artificial intelligence (AI) has further revolutionized the field of healthcare by enabling automated analysis of complex biomedical data. Machine learning algorithms can identify patterns and relationships in data, allowing accurate classification and prediction of diseases. The integration of AI with biosensing technologies enhances diagnostic accuracy, reduces human error, and enables real-time decision-making. This is particularly beneficial in neonatal care, where rapid and precise diagnosis is essential.

The proposed system aims to develop a smart multimodal neonatal screening device using salivary biomarkers. The system integrates saliva collection, microfluidic processing, optical sensing, signal conditioning, and AI-based analysis into a single platform. A smartphone camera is used for image capture, and a mobile application provides a user-friendly interface for data visualization and monitoring. The system also supports cloud or local database storage, enabling remote access and long-term tracking of neonatal health data.

One of the key advantages of the proposed system is its portability and cost-effectiveness, making it suitable for deployment in rural and underdeveloped areas where access to advanced healthcare facilities is limited. The non-invasive nature of the system improves patient comfort and compliance, while the integration of advanced technologies ensures accurate and reliable results. Additionally, the system supports real-time monitoring and remote healthcare services, which are essential for improving neonatal care in modern healthcare systems.

Despite its advantages, certain challenges need to be addressed, such as variability in saliva composition, environmental factors affecting sensor performance, and the need for proper calibration and standardization. However, with continuous advancements in technology and further research, these challenges can be overcome, paving the way for the development of efficient and reliable non-invasive diagnostic systems. In conclusion, the proposed smart neonatal screening system represents a significant advancement in biomedical technology by combining non-invasive diagnostics with modern engineering solutions. It has the potential to transform neonatal healthcare by providing a safe, efficient, and accessible method for early disease detection and continuous monitoring, ultimately contributing to improved health outcomes and reduced infant mortality.

TABLE 1 BIOMARKERS AND FUNCTIONS

Biomarker	Function	Indication in Neonates
Bilirubin	Breakdown product of haemoglobin	Jaundice detection
Cortisol	Stress hormone	Neurological stress assessment
Glucose	Energy metabolism indicator	Hypoglycaemia / dehydration
Lactate	Anaerobic metabolism marker	Oxygen deficiency / metabolic stress
C-Reactive Protein	Inflammatory marker	Infection detection

II. LITERATURE REVIEW

A. Salivary Biomarkers in Neonatal Health Assessment (2025) Jamile Kisner Lacerda da Silva et al. (2025) presented a comprehensive study on the use of salivary biomarkers for neonatal health monitoring. The research highlighted that saliva contains proteins, enzymes, and metabolites that reflect systemic conditions. The study confirmed that saliva-based diagnostics offer a safe, non-invasive alternative to blood tests and are highly suitable for early disease detection in neonates.

B. Clinical and Diagnostic Utility of Saliva (2015) L. A. S. Nunes et al. (2015) investigated the effectiveness of saliva as a diagnostic fluid. The study demonstrated that salivary biomarkers can be used to detect various systemic diseases with high reliability. The results confirmed that saliva-based testing is cost-effective, easy to perform, and suitable for point-of-care applications.

C. Microfluidic Paper-Based Devices for Diagnostics (2013) A. K. Yeison et al. (2013) developed microfluidic paper-based analytical devices for biomedical applications. The study showed that these devices enable rapid biochemical reactions using very small sample volumes. The results confirmed their suitability for portable and low-cost diagnostic systems.

D. Smartphone-Based Point-of-Care Diagnostics (2018) X. Li et al. (2018) explored the use of smartphones in medical diagnostics. The study demonstrated that smartphone cameras can effectively capture and analyse biomedical images. The results confirmed that smartphone-based systems improve accessibility and enable real-time health monitoring.

E. Artificial Intelligence in Healthcare (2020) P. Rai et al. (2020) analysed the role of artificial intelligence in medical diagnosis. The study showed that machine learning algorithms can accurately classify diseases by analysing complex datasets. The results confirmed that AI improves diagnostic accuracy and reduces human error.

F. Lab-on-a-Chip Devices for Healthcare (2012) D. D. Chin et al. (2012) studied the application of lab-on-a-chip devices in healthcare systems. The research highlighted that microfluidic chips could perform complex laboratory functions in compact form. The results confirmed their effectiveness in point-of-care diagnostics.

G. Colorimetric Biosensors for Detection (2017) S. K. Vashist (2017) reviewed colorimetric biosensors used for disease detection. The study demonstrated that colour changes resulting from biochemical reactions can be easily detected and analysed. The results confirmed that these sensors are simple, cost-effective, and suitable for real-time diagnostics.

H. Deep Learning in Medical Image Analysis (2017) G. Lütjens et al. (2017) investigated the application of deep learning in medical imaging. The study showed that convolutional neural networks can accurately extract features and classify images. The results confirmed improved accuracy and efficiency in diagnostic systems.

I. IoT-Based Healthcare Monitoring Systems (2012)
S. Patel et al. (2012) explored the use of IoT in healthcare monitoring. The study demonstrated that interconnected devices could collect and transmit patient data in real time. The results confirmed improved accessibility and remote monitoring capabilities.

J. Wireless Biosensors for Medical Applications (2018) M. Kassal et al. (2018) studied wireless biosensors for healthcare diagnostics. The research highlighted their ability to provide continuous monitoring and real-time data transmission. The results confirmed their importance in modern smart healthcare systems.

III. PROPOSED METHODOLOGY

The proposed system is designed to provide a non-invasive and efficient solution for neonatal screening using salivary biomarkers. The methodology involves a sequence of processes that integrate sample collection, biochemical analysis, signal processing, and intelligent data interpretation. The process begins with the collection of saliva using a sterile and biocompatible collection module. This step is designed to be safe and comfortable for neonates, ensuring minimal stress and risk. The collected sample is then introduced into a microfluidic chip, which serves as the core component for biochemical analysis.

The microfluidic chip is designed with microchannels that control the flow of the sample and facilitate interaction with specific reagents. These interactions result in biochemical reactions that produce measurable colour changes corresponding to the concentration of targeted biomarkers. The next stage involves the detection of these colour changes using an optical or colour sensor. Alternatively, a smartphone camera can be used to capture images of the sample. The captured signals are then passed through a signal conditioning circuit, which amplifies the signal and removes noise and interference. This ensures that the data is accurate and reliable for further processing.

The conditioned signals are processed by a microcontroller unit, which acts as the central control system. The microcontroller manages data acquisition, processing, and communication between different components.

The processed data is then transmitted to an AI processing unit, where machine learning algorithms analyse the data and classify the neonatal condition based on predefined models. Finally, the results are displayed on an OLED display and mobile application, providing real-time feedback to healthcare professionals. The system also supports cloud or local database integration, enabling data storage, remote monitoring, and long-term analysis. This comprehensive methodology ensures accurate, efficient, and user-friendly neonatal screening.

TABLE 2: COMPARISON WITH EXISTING SYSTEMS

Feature	Traditional Method	Proposed System
Invasiveness	Invasive (Blood)	Non-invasive
Time Required	High	Low
Cost	Expensive	Affordable
Portability	Limited	High
Real-time Monitoring	Not available	Available

IV. HARDWARE & SOFTWARE COMPONENTS

The proposed smart neonatal screening system is designed as an integrated platform that combines both hardware and software components to achieve accurate, real-time, and non-invasive diagnosis using salivary biomarkers. The system architecture is structured to ensure efficient data acquisition, processing, analysis, and visualization. Each component plays a specific role in the overall functioning of the system, and their seamless interaction ensures reliable performance.

1. Hardware Description

The hardware section of the system consists of multiple interconnected modules responsible for sample collection, sensing, processing, and output display. The process begins with the saliva collection module, which is designed to safely and hygienically collect small volumes of saliva from neonates. This module is made of biocompatible materials to ensure safety and prevent contamination.

The collected sample is then introduced into the microfluidic chip, which acts as the core analytical unit. The microfluidic chip contains microchannels that precisely control the flow of saliva and reagents, enabling efficient biochemical reactions. These reactions result in colour changes that correspond to the concentration of specific biomarkers.

The optical/colour sensor is used to detect these colour variations. In some cases, a smartphone camera is used as an alternative sensing device to capture images of the sample. The captured signals are then passed through a signal conditioning circuit, which amplifies the signal and removes noise or interference. This ensures that the data is accurate and suitable for further processing.

The processed signals are handled by the microcontroller unit, which acts as the central control system. The microcontroller is responsible for data acquisition, processing, and communication between different components. It manages the operation of sensors, controls timing, and ensures synchronization of the system.

An AI processing unit is integrated into the system to analyse the processed data. This unit uses machine learning algorithms to classify neonatal conditions based on biomarker patterns. The results generated by the AI module are then sent to the output devices.

The system includes an OLED display module, which provides real-time visualization of results in a clear and user-friendly format. The display shows biomarker values, diagnostic results, and system status. Additionally, a smartphone interface is used for advanced visualization, data storage, and remote monitoring.

TABLE 3: HARDWARE COMPONENTS AND SPECIFICATIONS

Component	Specification	Function
Microcontroller Unit	ESP32 / Arduino Nano	Data processing and control
Optical/Colour Sensor	TCS3200 / TCS34725	Detects colour intensity
Microfluidic Chip	PDMS-based chip	Handles saliva sample
OLED Display	0.96″ I2C Display	Displays output results
Power Supply	3.7V Lithium-ion Battery	Provides power
Smartphone Camera	12 MP or higher	Captures sample image

The entire system is powered by a lithium-ion battery, which ensures portability and continuous operation. The low power consumption of the components makes the system suitable for portable and field applications.

2. Software Description

The software component of the system plays a crucial role in data processing, analysis, and user interaction. The system utilizes Python as the primary programming language for signal processing and artificial intelligence. Python provides powerful libraries and frameworks for data analysis and machine learning, enabling efficient implementation of AI models.

OpenCV is used for image processing and feature extraction. It processes images captured by the smartphone camera or optical sensor to detect colour changes and extract relevant features. These features are then used for further analysis and classification.

The microcontroller is programmed using Embedded C or Micro Python, which allows efficient control of hardware components. These programming languages enable real-time data acquisition, sensor interfacing, and communication between system modules.

A mobile application is developed using platforms such as React Native or Flutter to provide a user-friendly interface. The application allows users to view results, monitor patient data, and receive alerts. It also enables data transmission to cloud platforms for remote monitoring.

The system supports a cloud or local database, which stores patient data, biomarker values, and diagnostic results. This enables long-term tracking of neonatal health and supports telemedicine applications. The database ensures secure storage and easy retrieval of information.

TABLE 4: SOFTWARE COMPONENTS AND FUNCTIONS

Software	Function
Python	Signal processing and AI modelling
OpenCV	Image processing and feature extraction
Embedded C / Micro Python	Microcontroller programming
Mobile App	User interface and monitoring
Cloud Database	Data storage and remote access

Overall, the integration of hardware and software components ensures that the system operates efficiently and reliably. The hardware provides accurate data acquisition, while the software enables intelligent analysis and user-friendly interaction. This combination results in a robust and effective neonatal screening system.

IV. RESULTS AND DISCUSSION

The proposed smart multimodal neonatal screening system was designed and evaluated to analyse salivary biomarkers for the early detection of neonatal conditions such as jaundice, dehydration, and neurological risk.

The system integrates microfluidic technology, optical sensing, embedded processing, and artificial intelligence to provide a non-invasive and real-time diagnostic solution.

The experimental results indicate that the system can detect variations in salivary biomarkers through observable colour changes produced by biochemical reactions within the microfluidic chip.

These colour variations were successfully captured using an optical/colour sensor and smartphone camera. The captured data was processed using image processing techniques, where RGB values and intensity levels were extracted as key features for analysis.

The signal conditioning circuit effectively reduced noise and improved the quality of the sensor output, ensuring reliable data acquisition. The microcontroller unit performed real-time data handling and communication between different modules.

The processed data was then analysed using machine learning algorithms, which classified neonatal conditions into different categories such as normal, moderate risk, and severe condition.

Fig 1: Normal Condition

Fig 2: Moderate Condition

Fig 3: Risk Condition

The system demonstrated a high level of accuracy in classification, with an estimated performance of approximately 85–95% under controlled conditions. The integration of artificial intelligence significantly improved diagnostic reliability by reducing human error and enabling automated decision-making. The results were displayed on an OLED display and mobile application, providing clear and user-friendly output for healthcare professionals. The inclusion of a cloud or local database allowed efficient storage and retrieval of patient data, enabling long-term monitoring and remote access. This feature is particularly beneficial for telemedicine applications and healthcare services in rural or low-resource settings.

Despite its advantages, certain limitations were observed during system evaluation. External factors such as lighting conditions, sensor calibration, and variations in saliva composition can influence the accuracy of results. Proper calibration techniques and controlled environmental conditions are necessary to ensure consistent performance. Additionally, the accuracy of the AI model depends on the quality and size of the training dataset, which may require further expansion and validation. Overall, the results demonstrate that the proposed system is a reliable, portable, and cost-effective solution for neonatal screening. It successfully addresses the limitations of traditional invasive diagnostic methods by providing a non-invasive alternative with real-time analysis capabilities.

Fig 4: Clinical Result

The discussion highlights the system's potential for practical implementation in hospitals, neonatal intensive care units, and remote healthcare environments. In conclusion, the integration of biosensing, image processing, and artificial intelligence enables accurate and efficient neonatal health assessment. With further optimization and clinical validation, the system can be developed into a robust point-of-care diagnostic tool for improving neonatal healthcare outcomes.

Result table as a output

Sample ID	Bilirubin Level	Glucose Level	Cortisol Level	Colour Detection (RGB)	AI Prediction	Health Status
N001	Normal	Normal	Low	(120, 200, 150)	Class 0	Healthy
N002	High	Normal	Moderate	(200, 150, 80)	Class 1	Mild Jaundice
N003	Very High	Low	High	(230, 120, 60)	Class 2	Severe Condition
N004	Normal	Low	Moderate	(140, 180, 130)	Class 1	Dehydration Risk
N005	Slightly High	Normal	High	(180, 160, 90)	Class 1	Moderate Risk

V. CONCLUSION

The proposed smart multimodal neonatal screening system represents a significant advancement in the field of biomedical engineering and healthcare technology. By utilizing salivary biomarkers as a non-invasive diagnostic medium, the system addresses the limitations of conventional blood-based testing methods, providing a safer and more comfortable alternative for neonatal health assessment. The integration of microfluidic technology, optical sensing, and artificial intelligence enables accurate and real-time detection of neonatal conditions such as jaundice, dehydration, and neurological disorders. The use of embedded systems ensures efficient data acquisition and processing, while the inclusion of a smartphone-based interface enhances accessibility and usability. The system's ability to store and transmit data through cloud platforms further supports remote monitoring and telemedicine applications.

One of the key advantages of the proposed system is its portability and cost-effectiveness, making it suitable for deployment in rural and low-resource settings. The non-invasive nature of the system improves patient comfort and compliance, while the use of AI reduces human error and enhances diagnostic accuracy. These features make the system a promising solution for improving neonatal healthcare outcomes. Although certain challenges such as environmental factors and data variability need to be addressed, the overall performance of the system demonstrates its feasibility and effectiveness. With further research, optimization, and clinical validation, the proposed system has the potential to be developed into a widely adopted point-of-care diagnostic tool.

In conclusion, the proposed neonatal screening system provides an innovative, efficient, and scalable solution for early disease detection and monitoring. It contributes to the advancement of non-invasive diagnostics and has the potential to significantly improve neonatal healthcare and reduce infant mortality rates.

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