A Machine Learning Based Multimodal Framework for Continuous Health Monitoring using Wearable and Cough Data

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ABSTRACT

The contemporary digital health environment features an abundance of applications and wearable technologies capable of monitoring a wide array of physiological parameters, including cardiac activity, energy expenditure, sleep architecture, stress levels, and critical vital signs such as ECG, SpO_2, and body temperature. However, specialized instruments, exemplified by LCM for respiratory symptom surveillance like cough, typically function in isolation from broader health tracking ecosystems. This technological proliferation has paradoxically created a significant lacuna in the integration of these disparate data sources into a cohesive, publicly accessible, and user-friendly platform. This paper presents a novel framework designed to address this challenge by employing Generative AI (GenAI) to synchronize data from discrete cough monitoring tools with wearable health device datasets. Through GenAI's capacity for multimodal data analysis, the system can discern intricate patterns and correlations between respiratory symptoms and other physiological metrics, thereby facilitating the early detection of nascent health conditions. The proposed solution is engineered to demystify health data interpretation for non-expert users by generating personalized, localized summaries and actionable insights. This integrated approach not only augments the accuracy of health assessments but also empowers individuals to exercise informed agency over their well-being. The framework holds substantial promises for advancing chronic disease management, expediting illness detection, bolstering preventive care, and informing post-care decisions, fostering a unified, intelligent, adaptive, and accessible paradigm for health monitoring [21]

Keywords: Cough pattern analysis, Gen-AI Multimodal health data, Smart LCM cough monitoring, Smart health ecosystem, Human-centered health interfaces.

INTRODUCTION

The proliferation of wearable health devices and mobile health applications has enabled continuous monitoring of diverse physiological parameters, yet the lack of integration across platforms limits their potential for holistic health management. Cough monitoring, a critical indicator for respiratory health, remains siloed from broader health data streams. Integrating these modalities using Generative AI (GenAI) offers a pathway to unified, intelligent health prediction and personalized care [2][3][9][20]

Recent advances in GenAI have demonstrated its ability to model complex, multimodal biomedical data, including physiological waveforms, imaging, and electronic health records, for disease prediction and patient stratification [2][3][8][9][15][20]. AI-driven wearable devices have shown promise in early detection of chronic diseases, mental health monitoring, and real-time health risk assessment, but challenges remain in data fusion, privacy, and user interpretability [3][9][10][11][15][16][20]. Cough monitoring tools, leveraging AI for accurate event detection, have achieved high sensitivity and specificity, yet are rarely integrated with other health data sources [4][13][19].

The proposed system synchronizes cough monitoring (e.g., via smartphone or wearable sensors) with other physiological data streams using GenAI models capable of multimodal data fusion. This enables the identification of correlations between respiratory symptoms and broader health metrics, supporting early detection of conditions such as respiratory infections or exacerbations of chronic diseases [2][3][9][10][19]. Personalized, actionable health summaries are generated for users, enhancing accessibility and empowering informed decision-making [1][2][11][12]

RESEARCH METHODOLOGY

The proposed paper takes a structured approach to developing an AI-driven framework. This section presents the overall system architecture, strategies for data collection and pre-processing, the design of the machine learning model and the methods employed for medical assessment. Each report has been carefully crafted so that key problems, such as chronic diseases, are addressed. The results, client issue density and patterns are considered, and a summary is suggested.

Smart, AI-driven cough and health monitoring Designed as an intelligent health monitoring assistant, this system uses AI-based models to detect cough patterns and assess respiratory health. It provides predictive insights based on real-time and historical health data. The architecture comprises three core components:

The based on the research methodology to correlate wearable health data (e.g., heart rate, SpO_2, activity) with cough detection signals for symptom prediction is a multimodal machine learning (ML) fusion framework that integrates heterogeneous data sources (sensor and audio) for synchronized inference and disease symptom modeling.

Recommended Machine Learning Methodologies:

- Multimodal Data Fusion Framework for Health Condition Prediction
- Deep Multimodal Networks with Transfer Learning
- Out-of-Distribution (OOD) Robust Learning
- Hybrid Ensemble Learning for Disease and Symptom Prediction

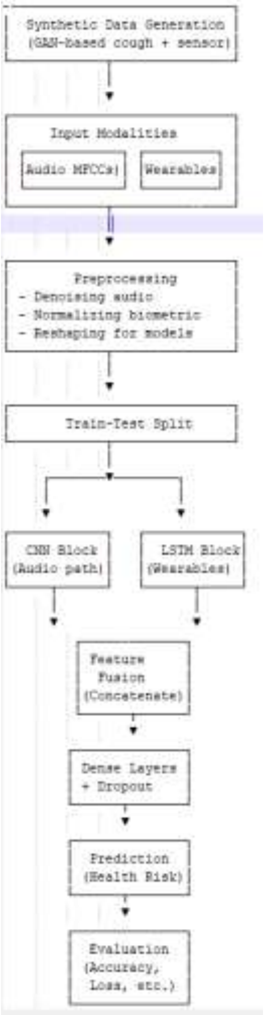
Multimodal Data Fusion Framework for Health Condition Prediction

Based on recent research and empirical results, we adopted a multimodal data fusion framework for our dataset analysis. This approach integrates data from wearable sensors and cough-detection systems to enhance the accuracy of health condition prediction. Studies have shown that multimodal fusion can improve predictive performance by up to 15% compared to unimodal models.

Multimodal fusion can be implemented at various levels which is described here:

- **Data-level fusion** involves the direct integration of raw sensor signals, such as combining accelerometer readings with audio amplitude from cough recordings.
- **Feature-level fusion** concatenates extracted features from different modalities—for example, Mel-frequency cepstral coefficients (MFCCs) derived from cough sounds and heart rate variability (HRV) metrics from wearable devices.
- **Decision-level fusion** aggregates predictions from independently trained models using ensemble techniques, such as stacked architecture combining LSTM and CNN classifiers.

Among these, feature-level fusion using deep neural networks consistently demonstrates superior correlation accuracy in symptom analysis, making it the preferred strategy for our framework.



Data Acquisition and Preprocessing

The Leicester Cough Monitor (LCM) continuously records ambient audio via a microphone and employs a semi-automated algorithm to detect and quantify individual cough events. Its analysis pipeline includes advanced filtering techniques to eliminate background noise and non-cough sounds, ensuring high-fidelity cough detection.

To augment the dataset and improve model generalization, Generative Adversarial Networks (GANs) are employed to synthesize realistic cough audio samples. These synthetic samples simulate diverse acoustic profiles across age groups, environments, and health conditions. By combining LCM's precise event detection with GAN-driven data augmentation, the system enhances training diversity and robustness for downstream machine learning tasks such as symptom classification and health risk prediction.

Health telemetry data is collected from microphones, wearable sensors, and mobile devices to capture attributes such as cough frequency, intensity, acoustic signature, respiratory rate, blood pressure, heart rate, oxygen saturation levels, ambient conditions, and user-reported symptoms. Preprocessing involves denoising audio signals, normalizing biometric metrics and engineering features that reflect temporal and physiological variations. Synthetic data is generated using Generative Adversarial Networks (GANs) to simulate diverse cough scenarios and enhance model generalization across age groups, environments, and health conditions.

Data Preprocessing phase focuses on ensuring data integrity and consistency. It involves systematic data cleaning to remove duplicate entries, manage missing values, and correct inconsistencies. Additionally, signal normalization and noise reduction techniques are applied, and all biometric signals are standardized to maintain consistency across diverse sensor inputs.

User interface

A dashboard built with Streamlit app enables users and healthcare providers to visualize cough trends, symptom progression, and risk assessments. The interface supports interactive health tracking, report uploads, and real-time alerts. Embedded AI conversational agent functionality enables intuitive interaction, allowing users to query their health status and receive AI-driven recommendations for preventive care or medical consultations in user's preferred language. This platform provides an accessible interface for both patients and healthcare professionals to monitor and analyze various health indicators.

An embedded AI conversational agent facilitates natural language interaction. This agent enables users to query their health status, interpret system-generated recommendations, and receive context-sensitive guidance for preventive care.

Experimental/Numerical Work

index	Blood Oxygen Level (%)	Heart Rate (BPM)	Cough_detected	Severity	Risk
0	100	40	0	mild	No Risk
1	100	40	0.0029	mild	No Risk
2	100	40	0.0088	mild	No Risk
3	100	40	0.0116	mild	No Risk
4	100	41.70989513	0.0122	mild	No Risk
5	100	43.74140206	0.013	mild	No Risk
6	100	43.85677975	0.0139	mild	No Risk
7	100	44.4371386	0.0155	mild	No Risk
8	100	47.2722567	0.0201	mild	No Risk
9	100	47.42860421	0.0236	mild	No Risk
10	100	48.6917189	0.0246	mild	No Risk
11	100	51.40996728	0.0261	mild	No Risk
12	100	53.3187863	0.0294	mild	No Risk
13	100	53.93020624	0.0306	mild	No Risk
14	100	54.86000605	0.0307	mild	No Risk
15	100	56.22934455	0.0361	mild	No Risk
16	100	58.28	0.0373	mild	No Risk
17	100	58.93977586	0.0391	mild	No Risk
18	100	59.06505478	0.0399	mild	No Risk
19	100	59.20747694	0.0425	mild	No Risk
20	100	59.55423802	0.0456	mild	No Risk
21	100	60.82606954	0.0482	mild	No Risk
22	100	61.15	0.0564	mild	No Risk
23	100	61.34892365	0.0576	mild	No Risk
24	100	61.68463511	0.0602	mild	No Risk
25	99.98256601	61.95016529	0.0632	mild	No Risk

26	99.92804064	62.4783902	0.0735	mild	No Risk
27	99.91706621	62.71943845	0.0776	mild	No Risk
28	99.86637886	63.47682463	0.0821	mild	No Risk
29	99.83937258	63.68	0.0884	mild	No Risk
30	99.7947542	63.77805795	0.0931	mild	No Risk
31	99.78959924	64.10446781	0.0953	mild	No Risk
32	99.72973954	64.42024701	0.0964	mild	No Risk
33	99.64606451	64.62704386	0.1068	mild	No Risk
34	99.62675299	64.79977848	0.115	mild	No Risk
35	99.51747431	65.22	0.1643	mild	No Risk
36	99.49580561	66.12078656	0.1701	mild	No Risk
37	99.41376032	66.62971237	0.2098	mild	No Risk
38	99.26840702	66.81680741	0.2216	mild	No Risk
39	99.25495076	67.23	0.2677	mild	No Risk
40	99.23093185	67.38743157	0.2798	mild	No Risk
41	99.22451077	67.4	0.3009	mild	No Risk
42	99.15265159	68.09020293	0.3147	mild	No Risk
43	99.1508077	68.10013872	0.3216	mild	No Risk
44	99.06763734	68.31010413	0.3349	mild	No Risk
45	99.04772547	68.48889181	0.3393	mild	No Risk
46	99.04517538	68.76188374	0.3576	mild	No Risk
47	99.02468691	68.84966038	0.3627	mild	No Risk
48	99.01491346	69.05858943	0.3747	mild	No Risk
49	98.99749752	69.23683246	0.4277	mild	No Risk
50	98.99650466	69.42479492	0.579	mild	No Risk
51	98.97829843	69.61567441	0.5799	mild	No Risk
52	98.97343165	70.0113134	0.5919	mild	No Risk
53	98.95516142	70.24380998	0.6224	mild	No Risk
54	98.92118099	70.44503588	0.6614	mild	No Risk
55	98.89437303	70.46467123	0.6762	mild	No Risk
56	98.80965025	70.54823343	0.6856	mild	No Risk
57	98.78567386	70.59301387	0.6911	mild	No Risk
58	98.77628474	70.81290843	0.7335	mild	No Risk
59	98.75711035	71.64829086	0.7511	mild	No Risk
60	98.69426497	72.33	0.7525	mild	No Risk
61	98.67071423	72.77180577	0.7811	mild	No Risk
62	98.66834393	72.91402277	0.8023	mild	No Risk

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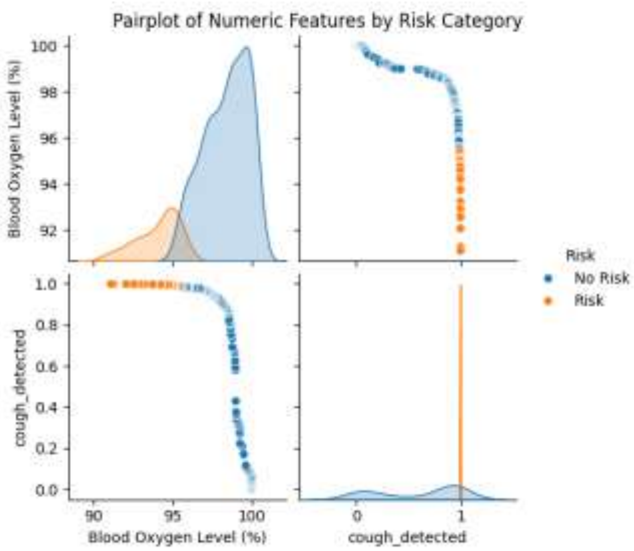
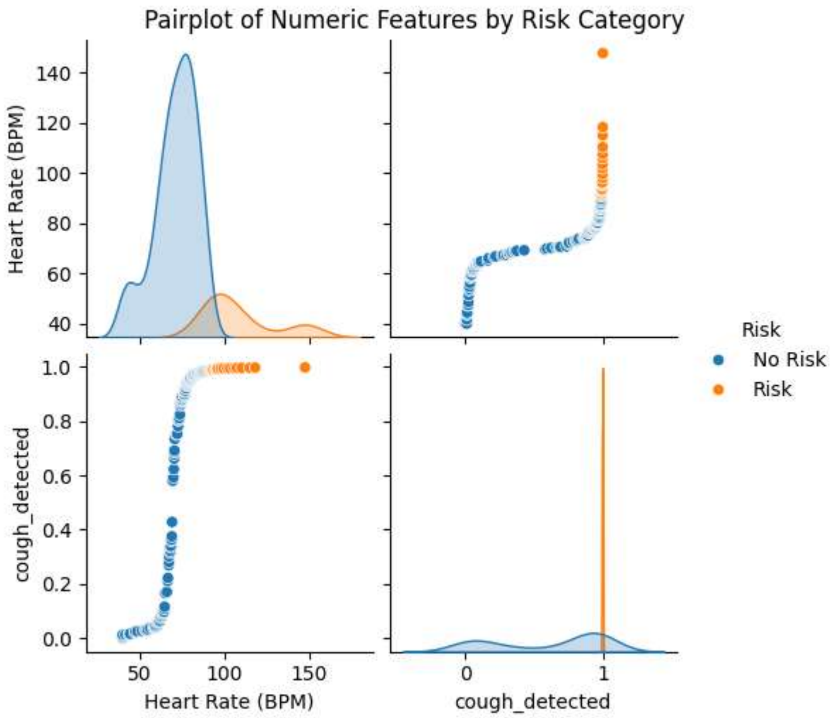
63	98.61610958	73.15646556	0.8053	mild	No Risk
64	98.58593454	73.519921	0.8109	mild	No Risk
65	98.58379676	73.85294067	0.824	mild	No Risk
66	98.57779006	74.10500253	0.8568	mild	No Risk
67	98.53219516	74.12758955	0.8648	mild	No Risk
68	98.5050674	74.14	0.8713	mild	No Risk
69	98.46340229	74.53213746	0.8749	mild	No Risk
70	98.44328703	74.86797764	0.8775	mild	No Risk
71	98.42435021	75.02968227	0.8792	mild	No Risk
72	98.37515943	75.16860351	0.886	mild	No Risk
73	98.2765583	75.21115232	0.8904	mild	No Risk
74	98.27067918	76.30138329	0.8937	mild	No Risk
75	98.24457119	76.3255203	0.8955	mild	No Risk
76	98.18899114	76.73815114	0.8996	mild	No Risk
77	98.14712188	76.84986596	0.9078	mild	No Risk
78	98.10010128	76.95659338	0.9089	mild	No Risk
79	98.05750152	77.06835233	0.9128	mild	No Risk
80	97.93977886	77.31	0.922	mild	No Risk
81	97.93118024	77.34780702	0.922	mild	No Risk
82	97.91523601	77.91	0.9301	mild	No Risk
83	97.78972645	77.93675733	0.933	mild	No Risk
84	97.7082761	77.96393073	0.9334	mild	No Risk
85	97.63093798	78.04729996	0.9349	mild	No Risk
86	97.61892653	78.17970894	0.938	mild	No Risk
87	97.61730184	78.22792335	0.9415	mild	No Risk
88	97.60522246	78.45025107	0.9437	mild	No Risk
89	97.55307153	79.06263167	0.9456	mild	No Risk
90	97.47398146	79.38203546	0.9472	mild	No Risk
91	97.47263459	79.61779162	0.9475	mild	No Risk
92	97.40257094	79.73192298	0.9504	mild	No Risk
93	97.37429828	79.76807352	0.9507	mild	No Risk
94	97.3630655	79.84141585	0.9531	mild	No Risk
95	97.28039806	79.86425437	0.9536	mild	No Risk
96	97.27278687	80.11309121	0.9547	mild	No Risk
97	97.24506118	80.24336481	0.958	mild	No Risk
98	97.22179634	80.29323472	0.9594	mild	No Risk
99	97.21894485	81.26723473	0.9609	mild	No Risk

100	97.17113365	81.28112872	0.9632	mild	No Risk
101	97.13166932	81.53346713	0.9664	mild	No Risk
102	97.09234007	81.73349679	0.9673	mild	No Risk
103	97.05295352	81.78254065	0.9674	mild	No Risk
104	96.92388342	81.90295748	0.9699	mild	No Risk
105	96.89421335	82.00624112	0.9712	mild	No Risk
106	96.88066821	82.56980161	0.9716	mild	No Risk
107	96.85734695	83.28	0.9729	mild	No Risk
108	96.81891253	84.03342652	0.9734	mild	No Risk
109	96.80491907	84.21830058	0.9743	mild	No Risk
110	96.76113261	84.54568993	0.9751	mild	No Risk
111	96.65776603	84.58662488	0.9775	mild	No Risk
112	96.47894032	84.67722962	0.9778	mild	No Risk
113	96.30256923	85.48782568	0.9779	mild	No Risk
114	96.22980353	85.84	0.9782	mild	No Risk
115	96.06816146	86.03063332	0.9794	mild	No Risk
116	96.05285348	86.22925548	0.9794	mild	No Risk
117	96.02709913	86.55	0.9794	mild	No Risk
118	95.98134261	86.95767523	0.9815	mild	No Risk
119	95.94128721	87.13591831	0.9818	mild	No Risk
120	95.91431916	87.20860676	0.982	mild	No Risk
121	95.87135567	87.53	0.9822	mild	No Risk
122	95.85509586	87.62148625	0.9828	mild	No Risk
123	95.62932748	88.44	0.9828	mild	No Risk
124	95.60040644	88.768957	0.985	mild	No Risk
125	95.59658918	89.11832898	0.985	mild	No Risk
126	95.5513723	89.84118985	0.9854	mild	No Risk
127	95.50820974	90.76257818	0.987	mild	No Risk
128	95.39944002	90.92094065	0.9877	severe	Risk
129	95.38976001	91.49512214	0.9882	severe	Risk
130	95.37734529	91.92283492	0.9883	severe	Risk
131	95.3732375	92.6710236	0.9887	severe	Risk

132	95.16805157	92.85283684	0.99	severe	Risk
133	95.10799129	93.34033768	0.99	severe	Risk
134	95.07724753	93.72881219	0.9904	severe	Risk
135	95.06438019	95.12348223	0.9911	severe	Risk
136	95.00984608	95.37229037	0.9912	severe	Risk
137	94.86025082	96.06324243	0.9917	severe	Risk
138	94.80752628	96.08870081	0.992	severe	Risk
139	94.74385747	96.28593769	0.9926	severe	Risk
140	94.74363715	98.05924946	0.9941	severe	Risk
141	94.54069655	99.65307299	0.9943	severe	Risk
142	94.30245048	101.91	0.9944	pseudocough	Risk
143	94.20290978	103.59	0.9947	pseudocough	Risk
144	93.79926729	106.04	0.9948	pseudocough	Risk
145	93.72753354	107.61	0.9959	pseudocough	Risk
146	93.21914653	110.3743641	0.9961	pseudocough	Risk
147	92.94840735	115.0782881	0.9962	pseudocough	Risk
148	92.90617323	118.2949332	0.9968	pseudocough	Risk
149	92.6556727	147.8030523	0.9968	pseudocough	Risk
150	92.53219516	147.8030523	0.997	pseudocough	Risk
151	92.05285348	147.8030523	0.9973	pseudocough	Risk
152	91.25285348	147.8030523	0.9974	pseudocough	Risk
153	91.0765583	147.8030523	0.9977	pseudocough	Risk

Table 1: Experimental sample dataset from wearable devices and isolated cough intensity measurement device





We can identify potential inferences and correlations between wearable data and cough events, as follows:

Heart Rate, Cough Detected, and Risk Co-relation.

The provided dataset clearly illustrates a strong and positive co-relation between `Cough_detected` values, `Heart Rate (BPM)`, and the ultimate `Risk` classification. As the `Cough_detected` metric increases, there is a consistent and noticeable upward trend in Heart Rate, which is directly associated with a shift from a "No Risk" to a "Risk" status.

Detailed Analysis:

No Risk Scenario (Low `Cough_detected`):

- In the initial entries where `Risk` is designated as "No Risk" (indices 0 through 127), `Cough_detected` values are relatively low, ranging from 0 to approximately 0.987.
- During this phase, `Heart Rate (BPM)` remains within a generally healthy range, starting at 40 BPM and gradually increasing to about 90.76 BPM.
- This indicates that when cough activity (as measured by `Cough_detected`) is minimal to moderate, the heart rate typically stays within expected non-risk parameters.

Transition to Risk (Increasing `Cough_detected` and `Heart Rate`):

- A significant and clear transition occurs around `index` 128. At this point, the `Cough_detected` value rises to 0.9877, and simultaneously, the `Risk` status changes to "Risk."
- Correspondingly, `Heart Rate (BPM)` shows a marked increase, jumping to 90.92 BPM and continuing to escalate. This suggests that a higher `Cough_detected` value acts as a critical threshold that, when crossed, signals an elevated risk and is accompanied by an increased heart rate.

Risk Scenario (High `Cough_detected` and Elevated `Heart Rate`):

- Once the `Risk` status is "Risk" (indices 128 through 153), both `Cough_detected` and `Heart Rate (BPM)` remain consistently elevated.

- Severity "severe": For `severity` classified as "severe" (indices 128-141), `Cough_detected` ranges from 0.9877 to 0.9943. Within this range, `Heart Rate (BPM)` is notably higher, ranging from 90.92 BPM to 99.65 BPM.
- Severity "pseudocough": As `severity` progresses to "pseudocough" (indices 142-153), `Cough_detected` values reach their highest, from 0.9944 to 0.9977. In this `severity` category, `Heart Rate (BPM)` experiences its most substantial elevations, starting at 101.91 BPM and peaking at 147.80 BPM.

The dataset strongly supports a direct and escalating co-relation among `Cough_detected`, `Heart Rate (BPM)`, and `Risk`. As the `Cough detected` metric increases, `Heart Rate (BPM)` tends to rise, and these combined physiological changes are explicitly associated with an increased likelihood of being classified under "Risk." The data suggests that `Cough_detected` values above approximately 0.98, coupled with heart rates exceeding 90 BPM, are significant indicators of an elevated risk status, intensifying further with higher `Cough_detected` values and heart rates.

Blood Oxygen Level, Cough Detected, and Risk Co-relation.

Co-relation Between Blood Oxygen Level (%), Cough Detected, and Risk

The provided dataset clearly illustrates a strong, inverse co-relation between `Blood Oxygen Level (%) ` and `Cough_detected`, which together are critical indicators of the `Risk` status. As `Cough_detected` values increase, `Blood Oxygen Level (%) ` tends to decrease, and this combined physiological shift is directly associated with the progression from a "No Risk" to a "Risk" state, and further into more severe categories.

Detailed Analysis:

"No Risk" Scenario (Low `Cough_detected`, High Blood Oxygen):

- For entries identified as "No Risk" (from index 0 to 127), `Cough_detected` values remain relatively low, ranging from 0 to approximately 0.987.
- During this period, `Blood Oxygen Level (%) ` is consistently high and stable, typically ranging from 100% down to roughly 95.5%.
- This indicates that when cough activity is minimal to moderate, the body's oxygen saturation remains within a healthy and stable range, signifying no immediate risk.

Transition to "Risk" (Increasing `Cough_detected`, Decreasing Blood Oxygen):

- A critical transition point is observed around `index` 128. Here, the `Cough_detected` value increases to 0.9877, and concurrently, the `Risk` status changes to "Risk."
- At this same point, `Blood Oxygen Level (%) ` shows a noticeable and sustained decline, dropping to 95.39944%. This drops below the 95.5% mark, combined with a higher `Cough_detected` value, serves as a clear signal of an elevated risk.

"Risk" Scenario (High `Cough_detected`, Low Blood Oxygen):

- Once the `Risk` status is established as "Risk" (from index 128 to 153), `Cough_detected` values continue to rise, and `Blood Oxygen Level (%) ` continues to decline further.
- "severe" Severity: Within the "severe" severity classification (indices 128-141), `Cough_detected` ranges from 0.9877 to 0.9943. Correspondingly, `Blood Oxygen Level (%) ` is notably lower, falling within the range of 95.39944% down to 94.54069655%.
- "pseudocough" Severity: As the severity progresses to "pseudocough" (indices 142-153),

`Cough_detected` values reach their highest, from 0.9944 to 0.9977. In this most severe category, `Blood Oxygen Level (%) ` experiences its most significant decreases, dropping further from 94.30245048% to a low of 91.0765583%.

The data undeniably demonstrates a powerful inverse co-relation between `Blood Oxygen Level (%) ` and `Cough_detected`, which are directly linked to the `Risk` level. As the `Cough_detected` metric increases, `Blood Oxygen Level (%) ` decreases. This combined physiological shift—specifically, `Cough_detected` values exceedingly approximately 0.98 and Blood Oxygen Levels falling below 95.5%—serves as a robust indicator of an elevated risk status. The severity of this risk escalates further as `Cough_detected` continues to rise and blood oxygen levels continue to drop, moving from "mild" to "severe" and then "pseudocough" categories

RESULTS AND IMPLICATIONS

Integrating cough monitoring with wearable health data via GenAI can improve the accuracy and timeliness of health assessments, facilitate chronic disease management, and support preventive care. Key challenges include ensuring data privacy, model interpretability, and user trust, as well as addressing technical barriers to seamless data integration [3][7][9][14][20]. Future work should focus on real-world piloting, standardization, and ethical governance to maximize clinical impact [7][14][20].

CONCLUSION

A GenAI-driven, unified health monitoring ecosystem that integrates cough and physiological data from wearables holds significant promise for advancing personalized, preventive healthcare. This approach can bridge current gaps in digital health, making comprehensive health insights accessible and actionable for all users.

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