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Investigating Risk Level in Maternal Mortality via a 3ConFA Feature Fused SMOTE-Tomek Balancing with Attention-Guided BiGRU Scheme: A Pilot Study

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ABSTRACT

Maternal health often transcends the overall physical, mental well-being of both a mother and the fetus through the duration of pregnancy and postpartum period. The crucial nature of provisioning adequate medicare during pregnancy cannot be over-emphasized – as it seeks to reduce the risk levels associated with maternal-and-neonatal deaths. With class-imbalance and dynamic chaotic features rippled across the domain dataset – models must be poised at improved generalization performance via the appropriate selection of features that will yield improved ground-truth for the target class. With vast amount of data acquired via sensor observations and clinic parameters – machine learning schemes have been successfully trained to gleans off valuable insights to medi-czars with proactive interventions for potential health risks prior its clinical manifestations. With early identification of potential health-related anomalies in maternal mortality risk levels – we posit a three-condition feature selection framework (3ConFA) that effectively hybrids the chi-square, information gain and decision tree recursive feature elimination modes – that ensures a hard-voting such that all three-mode feature selection criteria is utilized in the selection of final feature set of the explored dataset – to ensure that only features that meets all three-conditions are selected. With feature selection achieved via 3ConFA, and data balancing with SMOTE-Tomek – we utilize a hybrid attention-guided bi-directional gated recurrent unit in identifying the risk-level symptoms (predictors). Result shows that our attention-guided BiGRU ensemble yields F1 0.995, Accuracy 0.997, Precision 1.000, Specificity 1.000, Recall 0.998, and AUC 0.997 – to accurately classify all 253-cases of test-dataset. In addition, our proposed hybrid model outperformed the various benchmarks.

Keywords: Maternal Mortality, Infant Mortality, Prenatum, Postnatum, Gestational Diabetes,

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I. INTRODUCTION

Maternal mortality is best described as the death of women during pregnancy, post-pregnancy cum childbirth, or within six-weeks of the termination of a pregnancy (Ismail et al., 2017). This is especially true for rural-and-semi-urban areas with residents of low-income households – as pregnancy has since become a crucial public concern due to the limited availability of resources and provisioning of medicare infrastructure (Onoma, Ako, Anazia, Oghorodi, et al., 2025; Onoma, Ako, Ojugo, Geteloma, et al., 2025), the access to quality medicare (Tyler Morris et al., 2023), insufficient natal care (Pratama et al., 2025; Zuama et al., 2025), and maternal malnutrition (Setiadi, Ojugo, et al., 2025). These have remained the immediate causative for the rising trends in infant-and-maternal mortality – alongside the severe lack of healthcare czars (Razali et al., 2020), skilled birth attendants, and other essential healthcare resources (E. Ugbotu, Ako, et al., 2025). The World Health Organization (WHO) has dubbed maternal mortality a menace (Eranga, 2020) with many households in multi-dimensional poverty – as 1-in-42 women in Africa will likely die of associated risks (Ojugo, Ejeh, Akazue, Ashioba, et al., 2023). Nigeria accounts for 29% of global maternal mortality (i.e. 1,047 per 100,000 deaths) as compared to nations such as Australia and New Zealand with about 4-deaths per 100,000 live-births (Behera et al., 2022). Surprisingly, 65% of global maternal mortality is experienced in Africa (Jerbi et al., 2023) – and millions of women are constantly, still exposed to pregnancy-induced and livebirth risks. Advances in medicare frontiers have ushered in improved healthcare infrastructure (Setiadi, Nugroho, et al., 2024), and rippled across a global drop by 34% between 2005 and 2023 in maternal mortality (Al-Nbhany et al., 2024), and a decline of about 95-percent in middle- cum low-income nations.

While, skilled healthcare professionals via their expertise, easily prevent complications that save lives – symptoms such as hypertension (Odiakaose et al., 2024), diabetes (Ojugo et al., 2015b) and other pregnancy-induced complications (Joshi & Dhakal, 2021) yields a range of triggers that advent closer monitoring of pregnant women and urgent alert of experts, soon as symptoms are flagged to avoid fatal outcomes for both a mother and her fetus (Ojugo & Otakore, 2018a). Other triggers of change in clinical parameters can include BMI, pre-existing diabetes, blood pressure (Eboka, Aghware, et al., 2025; Eboka, Odiakaose, et al., 2025), blood sugar, etc, which allows care experts to investigate cases of high-risk in pregnancies via a comprehensive monitor. These complications, if unmonitored and unmanaged – morphs as life-threatening conditions to infant and maternal mortality (Agboi, Emordi, et al., 2025). Monitoring of vital signs as critical clinical parameters like underlying diabetes, hypertension, blood pressure, etc – are essential predictors for early risk-levels detection for maternal mortality (Ako et al., 2025); whereas, other features like mental health (depression) impact both mother-and-baby, and require drug-possible support. Diabetes and blood sugar requires urgent control to prevent high birth-weights or preterm delivery (Joseph et al., 2022; Manickam et al., 2022); while, hypertension can cause risks like eclampsia, preeclampsia (restricted blood-flow) to a fetus (Zetterman et al., 2024), and ultimately, maternal hemorrhaging (Akazue, Okofu, et al., 2024; Ojurongbe et al., 2023).

These are significantly, complex and dynamic complications that needs constant monitoring and alert of healthcare professional. to prevent accompanying severe risks to both the mother and fetus (da Costa et al., 2021). Advances in medicare with the integration of diagnostic tools, wearable technologies, and mental health screening procedures – have all sought to enhance real-time monitoring (Malasowe, Aghware, et al., 2024; Malasowe, Ojie, et al., 2024) with timely-sensitive interventions. Sensor-based supports offers a non-invasive, continuous monitoring that that aligns with the United Nations Sustainable Development Goals 3 (Good Health and Well-Being), SDG 9 (Industry, Innovation and Infrastructure), and SDG 10 (Reduced Inequalities) (Ojugo & Yoro, 2021). Patients' comprehensive care eased with techs have become crucial to reduce the accompanying risk-levels with pregnancy vis-à-vis improve positive outcomes in risky pregnancies. The monitor and alert of clinical criteria has become crucial as a comprehensive dataset will yield greater insights of detailed health-profile for pregnant mothers (Qasrawi et al., 2022). This, in turn will enhance our understanding of pregnancy-risk issues (Throm et al., 2025), equip healthcare professionals (Soni et al., 2020) with informed decisions for improved diagnostic accuracy (Binitie et al., 2025; Ejeh et al., 2024), and proffer the needed-support for development and deployment of predictive models (Ifioko et al., 2024; Muhamada et al., 2024; Yoro et al., 2025).

The continuous monitoring via sensor-based units offers data acquisition for a patient's baseline health status (Bolívar, 2013). The acquired metrics readings provision early warning of symptoms that aids the formulation of a tailored treatment plan and dissuade a complete metastasis as close to the source of the plausible disease (Odiakaose et al., 2025). The use of machine learning (ML) in medical data analysis to effectively recognize anomalies that helps us glean off insights into emergent issues. MLs have become veritable tools for disease prediction, identification and classification. As trained, they are broadly classified into: traditional machine learning schemes (TMLS) (Onoma, Agboi, Geteloma, Max-egba, et al., 2025), improved deep learning (IDLA) (Ojugo, Akazue, Ejeh, Ashioba, et al., 2023; Oppenheimer et al., 2024), and ensemble learning schemes (ELS) (Binitie et al., 2024). The flexibility and robustness of TMLS does efficiently and succinctly help it to learn the underlying changes in data patterns to help decode selected predictors that fastens model design and construction that eases the identification of outliers. A major pitfall of the TMLS is their adaptability in resolving the imbalanced nature of the explored dataset. To overcome this, the IDLA exploits cascaded neural networks used to capture chaotic, and high-dimensional micro data-points within a problem domain (Setiadi, Sutojo, et al., 2025). IDLA is restricted in its use due to its poor generalization from the vanishing gradient problem. Its variants seek to resolve this via the use of input-gates to controls the flow structure, and yield adaptability ease of its long-term dependencies (Schwertner et al., 2022). Its other demerits that may also restrict its usage includes: (a) its inability to handle larger dataset, and (b) longer train time to converge (Borchert et al., 2023; Eboka, Odiakaose, et al., 2025; Yoro & Ojugo, 2019a).

A further quest in hybridization results in ensemble learning scheme (ELS), which tactically fuses TMLS and IDLA, to yield a stronger learner with enhanced performance (Nayak et al., 2025; Setiadi, Susanto, et al., 2024). It leverages the predictive capability of both approaches to avoid model overfit with enhanced generalization for a comprehensive knowledge of the task (Islam et al., 2021; E. V. Ugbotu, Aghaunor, et al., 2025; E. V. Ugbotu, Emordi, et al., 2025). Its challenges include (Agboi, Onoma, et al., 2025; Malasowe, Edim, et al., 2024): (a) structural conflicts that determines the mode of fusion, and branch-off that points the end of one model onto the other, and (b) data-encoding conflicts that determines the conversion of data (i.e. binary-octal-decimal-hex schemes) as easily understood from one model to another – and easily resolved via One Hot-Encoding mode (Aghaunor, Agboi, et al., 2025; Ojugo & Eboka, 2018c; Omoruwou et al., 2024).

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This study contributes thus: (a) addresses existing gaps while proffering an extensive dataset of pregnant women receiving care at the Asaba Specialist Hospital in Delta State (Nigeria), (b) the sensitive nature of medical analytics with selected features for identifying maternal mortality - should provide a model with relevant predictors for the effective identification of the target class, (c) resolve dataset imbalance so that explored model is sensitive to account for the impact of the minority-class (Aghaunor, Omede, et al., 2025) that should not be ignored. Our study includes: Section 1 introduces subject with gaps for the study, (b) Section 2 unveils the proposed method – and leans on data collection, pre-processing, 3ConFA feature fusion, data split-balance-normalize, the model construction, its training and validation, and (c) Section 3 – discusses the experimental results obtained as evidence in a broader context of maternal mortality risk level dataset.

2. MATERIAL AND METHOD

The proposed transfer learning approach is seen as in Figure 2.

Step-1 – Data Gather: We explore the UCI Maternal Mortality Risk Level dataset (Simegn & Degu, 2025) available on [web]: https://data.mendeley.com/datasets/p5w98dvbbk/1. It consists 1014-data with features such as age, body temperature, body mass index, systolic and diastolic pressure, medical history, mental health status, diabetes, heart rate, clinical observations, etc. Records are distributed into high-risk 272-records, medium-risk 336, and low-risk 406 classes as in Figure 2 – whereas, the dataset risk-level features are seen as in Figure 3, with a description of the dataset is in Table 1.

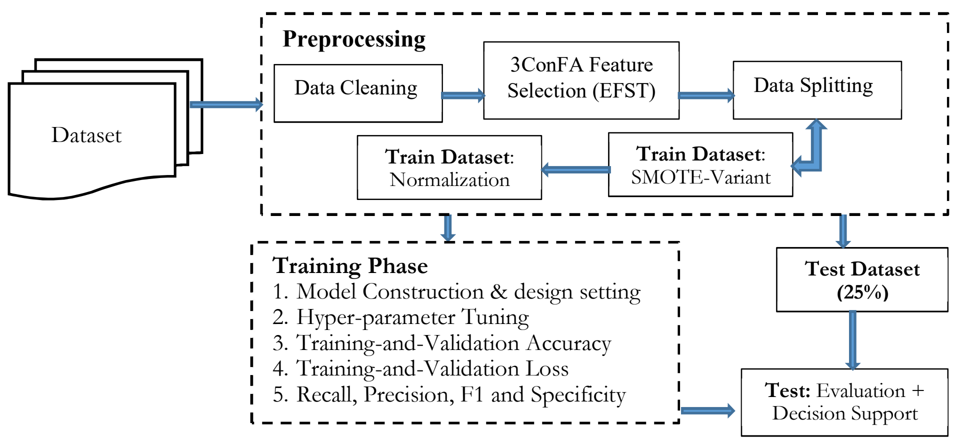

Figure 2. Proposed Attention Guided BiGRU methodology for Maternal Mortality

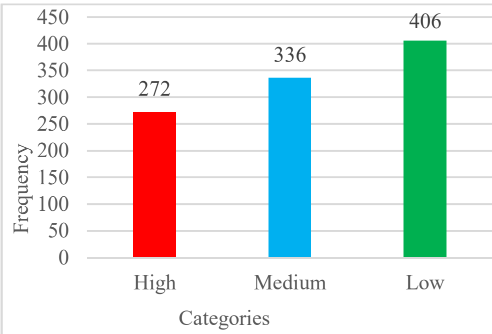

Figure 2. Dataset Plot by Risk-levels

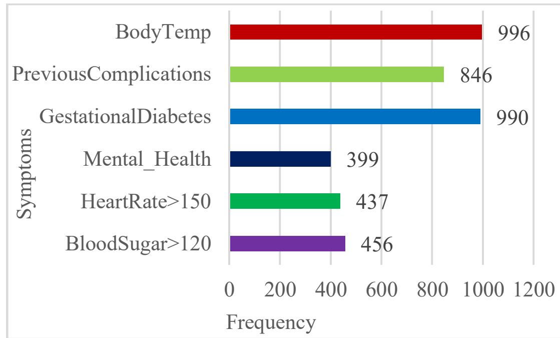

Figure 3. Dataset Plot by Symptoms

Table 1. Maternal Mortality Dataset

Parameters	Description	Data Type
age	Age in years when woman was pregnant	integer
systolicBP	Upper value of blood pressure in mmHg	integer
diastolicBP	Lower value of blood pressure in mmHg	integer
bmi	Body mass measures a patient fat for weight and height (kg/m^2)	integer
bloodSugar	Blood molar concentration in mmol/L	integer
bodyTemperature	Body temperature of the patient in degrees Fahrenheit	float
PreexistingDiabetes	Patient has a history of diabetes (0: No, 1: Yes)	binary
gestationalDiabetes	Patient has gestational diabetes during pregnancy (0: No, 1: Yes)	binary
mentalHealthStatus	Patient's has history of mental challenge (0: No, 1: Yes)	binary
MMSE	Mini-mental state exams (0-to-30) – lower score as impairment	float
heartRate	Patient's sleep time and quality ranging from 4-to-10	float
previousComplications	Patient has history of past chronic conditions (0: No, 1: Yes)	binary
confidentialReportxxx	Doctor-In-Charge confidential report	XXXConfid
riskLevel	Overall risk level of patient based on clinical parameters	binary

Step-2 – Pre-processing cleans up the dataset by expunging redundancies to yield integrity, and removes missing values to yield quality. The dataset had no missing values cum records. Thus, it was then encoded using the one-hot encoding technique mode that transforms categorical data into its equivalent binary forms (Ojugo & Otakore, 2018b, 2020; Ojugo & Yoro, 2013).

Step 3 – Feature Selection via Three Condition Feature Aggregation: Model training and validation for disease risk identification (Ojugo et al., 2021; Ojugo & Ekurume, 2021) is heavily dependent on the selected features, used by the explored model as predictors for ground-truth (Li et al., 2025; Ojugo et al., 2013). With large data collected at training – certain features are relevant for improved generalization; while other docile feature(s) degrade performance rather than enhance it. Here, we utilize the Three Conditions for Feature Aggregation (3ConFA) model (Asuai et al., 2025) that reduces a dataset's dimensionality whilst retaining essential predictors needed to effectively train/validate the explored model (Ojugo & Otakore, 2020; Ojugo & Yoro, 2013). Our 3ConFA scheme utilizes an ensemble feature selection technique that hybrids into a single mode – multiple feature selection modes to yield fastened model construction and improved model performance (Akhutie-Anthony et al., 2025). The 3ConFA model minimizes noisy (features) bias to ensures that only relevant features are retained (Ghasemieh et al., 2023).

Our 3ConFA curates an optimal number of predictors by aggregating the various modes to optimize the utilized ML, whilst decreasing model over-parameterization and complexity (Onoma, Ugbotu, Aghaunor, Agboi, et al., 2025; Onoma, Ugbotu, Aghaunor, Odiakaose, et al., 2025). Our 3ConFA fuses the filter (infoGain and chiSquare) and wrapper (recursive feature elimination) modes to iteratively remove irrelevant features via the EFST feedback (Akazue, Debekeme, et al., 2023; Akhutie-Anthony et al., 2025).

The 3ConFA EFST approach is explained thus:

1. The filter-mode Chi-square test evaluates the statistical independence between a feature f and its target class C – measuring the degree of association between observed and expected frequency. A higher X^2 implies stronger correlation of the feature with its target, and suggests higher feature relevance (Ako et al., 2024; Onoma, Agboi, Ugbotu, Aghaunor, et al., 2025). As in Equation 1 – X^2 value is computed with O_i as observed frequency of co-occurrence between a feature value and the target class, E_i is the expected frequency assuming independence between feature and class, and $\sum$ is the summation over all categories.

$$X^2 = \sum \frac{(O_i - E_i)^2}{E_i} \qquad Equation\ 1$$

2. The filter-mode Information Gain – measures how much a feature f reduces the uncertainty (entropy) in a target class C – by ranking all the selected features based on their ability to split a dataset into more homogeneous subsets (Akazue, Asuai, et al., 2023). Expressed as in the Equation 2 – it yields a difference between the entropy of the target variable (prior split) and the conditional entropy (after split based on the feature) as thus: (a) it first computes entropy for the target class to quantify its overall uncertainty as in Equation 2a, (b) it measures the residual uncertainty after partitioning the data based on a given feature using conditional entropy as in Equation 2b, and (c) it determines the reduction in uncertainty attributable to that feature, defined as the information gain (Equation 2c). A feature is deemed relevant if its IG value is greater than or equal to a predefined threshold.

$$H(C) = -\sum_i P(C_i) \log_2 C_i \qquad Equation\ 2a$$

$$H(C|f) = -\sum_j P(f_j) \sum_i P(C_i|f_i) \log_2 (C_i|f_i) \qquad Equation\ 2b$$

$$IG(f) = H(C) - H(C|f) \qquad Equation\ 2c$$

3. The wrapper-mode Decision Tree Recursive Feature Elimination (DT-RFE) select predictors by recursively eliminating the least relevant features based on its decision tree's Gini importance score and/or its mean decrease in impurity (Suruliandi et al., 2021; Tanimu et al., 2022). With model initially trained – it then ranks all features by importance (Ojugo & Eboka, 2020) with the least relevant features removed at each iteration. Model is retrained until the most relevant features remain as in Equation 3 – via considerable feature interactions and real-time performance feedback with feature elimination (Ojugo et al., 2015a).

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4. The Aggregation Conditions for 3ConFA – The workings of the 3ConFA-EFST lies in its three conditions, each of which addresses an aspect of feature fusion cum aggregation structure. These are further explained on the premise that a feature is retained in the final-set if and only if it satisfies all three conditions below (Ojugo, Odiakaose, Emordi, Ejeh, et al., 2023):
   a. **Condition-1** yields infoGain-Threshold, and IG-score of a feature must be greater than the average IG threshold – to ensures that only features significantly reducing class entropy are retained as expressed in Equation 3.

$$IG(f) \geq h_1 \qquad Equation\ 3$$

   b. That for its **Condition-2** – its X^2 feature computed threshold must exceed the average chi-square value (h_2) – and implies that the feature statistically yields a more meaningful correlation with the target class as expressed in Equation 4.

$$X^2(f) \geq h_2 \qquad Equation\ 4$$

   c. That for its **Condition-3** – the selected feature must be selected in the final iterations of the RFE eliminations – affirming its higest importance score, and that the feature also yields a more meaningful correlation with the target class as expressed in Equation 5.

$$RFE(f) \geq h_3 \qquad Equation\ 5$$

Algorithm Listing 1 for the proposed 3ConFA approach

Input: Features {f1,f2,...,fn}; Selection methods: infoGain, chiSquare, DT-RFE; Base Estimator: decisionTree,
Output: Threshold-Estimators α, β (for IG and X^2 aggregation); Optimal feature subset X
initialization: set X ← ∅ with temporary sets: s_1, s_2, s_3 ← ∅;
infoGain:
compute IG(*f*) (i.e. feature-IG)
find mean IG: $h_1 = \frac{1}{n}\sum IG(f_i)$ && select features: $S_1 = (f_i\ |IG(f_i)) \geq \alpha.h_1)$
chiSquare:
compute each feature X^2 value using Eq. 1
Find mean X^2: $h_2 = \frac{1}{n}\sum X^2(f_i)$ && select features: $S_2 = (f_i\ |X^2(f_i)) \geq \beta.h_2)$
DT-RFE:
initialize F ← D, baseModel ← decisionTree
Iteratively: train model on current features F
rank features by importance && remove lowestRanked *k*-features
re-evaluate until stopCriteria reached && finalFeatureSetSelected S_3
featureAggregation
for each feature f ← D: $if\ f\ \in S_1 \cup S_2 \cup S_3\ then\ X = X \cup \{f\}$ with optimal votingMajority across S_1, S_2, S_3
adjust thresholds α, β if performance is inadequate && repeat infoGain, chiSquare, DT-RFE & featureAggregation
end

With the computed thresholds set for all three conditions as in chi-square, Information Gain and Decision Tree Recursive Feature Elimination (Geteloma et al., 2024b, 2024a) – a feature is only included in the final feature-set selected (X) if and only if all three conditions are satisfied or met as in Table 2, with the feature importance as in Figure 4. The most important features yield the features with the highest values tending to 10.

Table 2. The 3ConFA Feature Fusion Selection

Parameters	ChiSquare	Info-Gain	DT-RFE	3ConFA Score	Selected
age	9.356	0.40804	5	3/3	Yes
systolicBP	13.36	0.59099	2	3/3	Yes
diastolicBP	10.041	0.77645	5	3/3	Yes
bmi	9.956	0.54823	3	3/3	Yes
bloodSugar	10.001	0.41518	8	3/3	Yes
bodyTemperature	4.248	0.78291	10	1/3	No
urinalysis	2.470	0.65961	11	1/3	No
PreexistingDiabetes	9.470	0.65961	11	3/3	Yes
gestationalDiabetes	10.492	0.41629	6	2/3	No
mentalHealthStatus	5.372	0.70898	8	3/3	Yes
MMSE	4.222	0.79356	3	3/3	Yes
heartRate	9.258	0.69636	9	2/3	No
previousComplications	9.029	0.42146	6	3/3	Yes
confidentialReportxxx	1.891	0.59653	3	1/3	No
riskLevel	3.092	0.45690	9	3/3	Yes

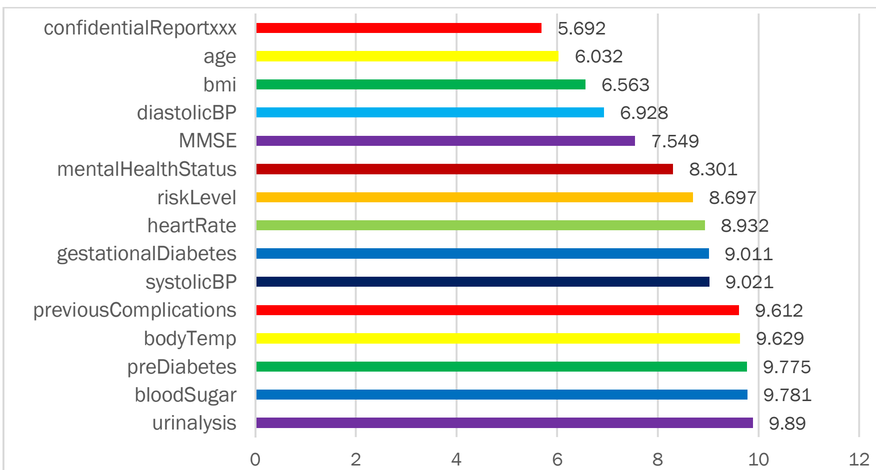

Figure 4. Feature Importance arranged by ascending order

Step 4 – Data Split/Balance: First, dataset is split into train (75%, or 760-data), and test (25%, or 254-data). Balancing resamples a dataset, interpolating its nearest neighbour to create synthetic (augmented) data that evenly repopulates a pool. While, the undersample mode (removal of data from a pool) is restrictive in its usage – studies utilize the oversample (augment) mode to yield techniques such as the adaptive synthetic (ADASyn) and synthetic minority oversampling (SMOTE) with its variants (Okpor et al., 2025). Here, we adapt the SMOTE-Tomek variant (Ojugo et al., 2014; Ojugo & Eboka, 2018a), a fusion of the SMOTE-oversample with Tomek undersample as in (Aghware et al., 2025) and seen in Figure 4.

To balance robustness and performance, granting the model the ability to learn intrinsic changes as they occur with improved generalization, data split is often a tradeoff: (a) influenced by the need for a more robust model, which favors a train-test ratio of 75%:25% (Ojugo & Eboka, 2019), or (b) influenced by the need for improved performance as guided by the model complexity, larger dataset size and other features, which favors the 80%:20% approach (Okofu, Akazue, et al., 2024; Okofu, Anazia, et al., 2024).

For this model, we choose the 75%:25% ratio due to the small nature of the explored dataset with 1,014-records so that we can ultimately have a more robust evaluation on diverse unseen held-out (test) data, address flexibility in feature selection for a more adaptive assessment with more accurate and less bias model generalization as in Figure 5 – whereas the SMOTE-Tomek data balanced plot is as in the Figure 6. In addition, with the train-set is still unbalanced (Akazue, Edje, et al., 2024; Okpor et al., 2024), we performed normalization via Equation 6 as in Figure 7.

$$z = \frac{x - \mu}{\sigma} \qquad Equation\ 6$$

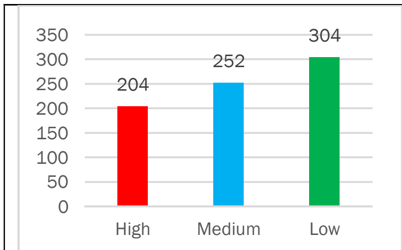

Figure 5. Training data plot

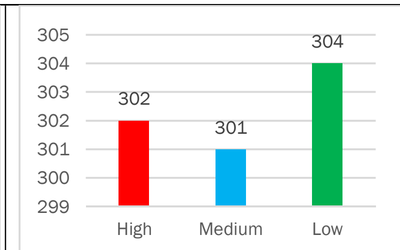

Figure 6. Balanced plot

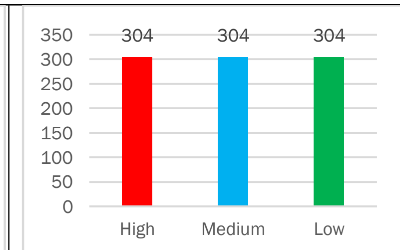

Figure 7. Normalized plot

Step-5 – Attention-Guide BiGRU: The utilization of ML schemes in deployment of medical apps for early detection of risk-levels (with maternal mortality) have sought to explore various techniques that seek to improve generalization performance (Parikh et al., 2019). Studies in behavioural risk detection have explored a variety of dataset (Mojumdar et al., 2025). While, risk identification is quite a challenging feat, accuracies range from [0.69, 0.89] (El Massari et al., 2022) with crucial factors that degrade performance to includes: (a) homogeneity complexity that results in dataset imbalance, (b) model sensitivity to hidden patterns with adaptive predictor bias, and (c) data leakages via non-adaptive model (Ojugo & Okobah, 2018; Yoro & Ojugo, 2019b). Thus, we utilize the attention-guided bi-directional gated recurrent unit, explained as in Figure 8 explained as thus (Aghware et al., 2024; Al-Hammadi et al., 2024; Ojugo et al., 2013, 2014; Reinke et al., 2023):

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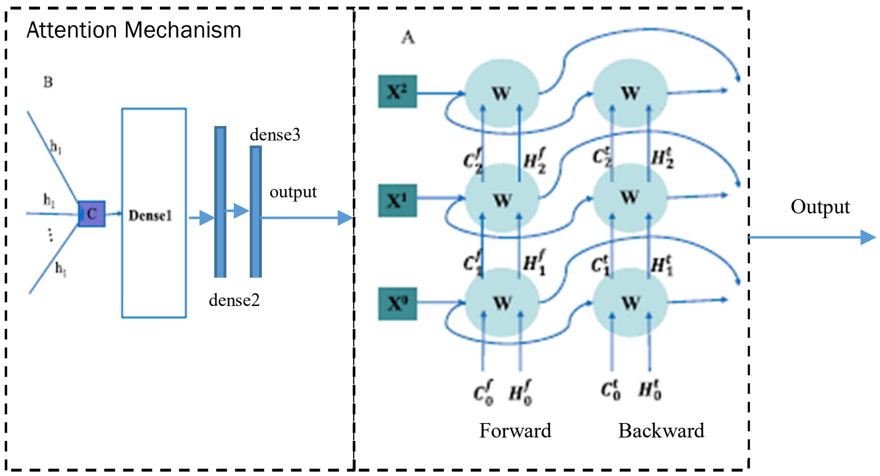

Figure 8. Schematics diagram of the Attention-Guide BIGRU structure

The BiGRU Model: BiGRU yields a simpler RNN (Yao et al., 2022) that overcomes the vanishing gradient problem by fusing the input and forget gates into a single update gate. This, reduces the number of predictors to be trained (Omede et al., 2024), and speeds up model construction cum training without trading off its memory. Its 2-way processing captures the before/after context in each record via its Update and Reset gates as in Equations (7)-(8) respectively (Otorokpo et al., 2024; Oyemade & Ojugo, 2020) with u_t as update gate, σ is sigmoid function, W is weight matrix, W_u is weight of update gate, h_{t-1} as hidden state in previous time, x_t is input at time t, r_t is reset gate, $\bar{\bar{h}}_t$ is new hidden state value for its memory cell, and h_t is updated hidden state at time t. With bidirectional data – the model improves contextual understanding of all data dependencies with carefully tuned hyper-predictor to yield a greater balance for train speed, result convergence, memory requirements, enhanced accuracy, and task distribution (Kumar et al., 2025; Said et al., 2023). Model configuration is seen as in Table 3.

$$u_t = \sigma(W_u[h_{t-1}, x_t]) \quad Equation\ 7a$$
$$r_t = \sigma(W_r[h_{t-1}, x_t]) \quad Equation\ 7b$$

$$\bar{h}_t = tanh(W[r_t * h_{t-1}, x_t]) \quad Equation\ 8a$$
$$h_t = \left(u_t * h_{t-1}(1 + u_t) * \bar{\bar{h}}_t\right) \quad Equation\ 8b$$

Table 3. The BiGRU Design Configuration

Features	Value	Description
RNNLayer	Bidirectional (GRU(64))	Bidirectional RNN: 64-GRU (1st) and 32-GRU (2nd)
returnSequence	True (for first layer)	Returns entire output sequence for the first layer
inputShape	xtrainScaledShape[1],1	Same length as predictors in xTrainScaled
denseLayer	ytrainResampledMax()+1	Same units as classes in yTrainResampled output layer
activation	Softmax	Activation function output for multi-class classification
optimizer	Adam	learnRate=0.001, beta_1=0.9, beta_2=0.999, epsilon-1e-07
lossFunction	categorical_crossentry	Loss function for multi-class classification

Attention-based Mechanism has rapidly become an efficient mode to improve the performance of models via selective knowledge of a task – so that the model can focus only on the most relevant data. It equips our BiGRU to focus on varying relations between features in our explored dataset, and to evaluate how important these relations are (Vaswani et al., 2017). With inputs accepted from its address key – the attention scheme assesses if stored parameters (i.e. bmi, systolicBP, diastolicBP, diabetes, etc) are associated with its query. It then computes similarities, and checks for anomalies that spikes its riskLevel metric in the multi-key addresses. Next, it computes the Query correlation, and adds the attention-weights vector to ascertain the final value(s).

Each feature importance is weighed against other features in the record (Çetin & Öztürk, 2025). We combined the self-attention mechanism with the BiGRU in parallel, which equips the model to avoid the conflict in probability that certain feature information will be lost. This helps with detection accuracy cum efficiency of the proposed transfer-learning so that the model can grasp the relations between each element in the data vis-à-vis assess their importance amidst other elements as it focuses on predictors as crucial parts of the input data sequence. Our attention mechanism uses the max-pooling to extract key knowledge that captures the dataset's feature diversity and complexity. In addition, the weighted feature maps are aggregated to yield the net final outcome. The network automatically adjusts to focus on the more important channels (Datta et al., 2021).

Step 6 – Train/Cross Validation is initialized with default configuration to ensure the collective knowledge to identify intricate data. Training blends synthetic with original data to guarantee its comprehensive learning with improved adaptability to various configurations (Setiadi, Muslikh, et al., 2024).

4. RESULTS AND DISCUSSION

4.1. Model Generalization Performance

With our resultant sub-dataset favouring 75% for train (i.e. 760-data), and 25% for test (i.e. 254-data) – Figure 9 shows both training-and-validation accuracy and loss plots. For the training-and-validation accuracy plot – the proposed model witnesses a steady rise from 0.845 in its second epoch, to 0.998 at its 52nd epoch. Conversely – with this significant learning at training, the proposed model in addition yields a sharp decrease in its training-and-validation loss from 0.236 also in the 2nd epoch, to a stable 0.100 in the 59th epoch as in the Figure 4.

For a comprehensive evaluation devoid of overfit, we use a 5-fold partition for the train-dataset obtained via SMOTE-Tomek, and a final evaluation on the held-out test (25%) as in Table 4. The proposed attention-guide BIGRU yields Accuracy 0.997, Recall 0.998, Precision 1.000, F1 0.995, Specificity 1.000 and AUC 0.997. Its high its Specificity of 1.00 implies that the model effectively recognizes risk-levels predictors, and that no benign data was misclassified for the unseen (test) data. Its AUC 0.997 implies that the model was able to differentiate between the benign and malignant records.

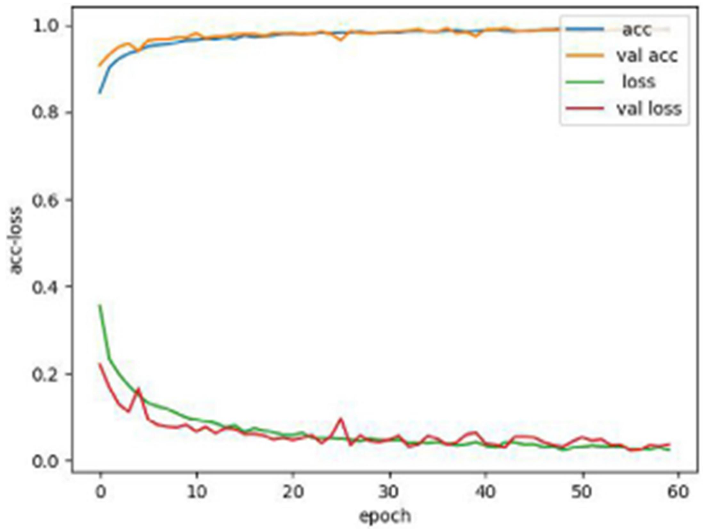

Figure 9. Model Train-and-Validation Accuracy-and-Loss

Table 4. Attention-Guided BiGRU Performance Metrics

Models	5-Fold Training with Validation					Held-Out Test Dataset
	Fold-1	Fold-2	Fold-3	Fold-4	Fold-5	
Accuracy	0.991	0.981	0.997	0.998	1.000	0.997
Recall	0.981	1.000	0.975	0.976	1.000	0.998
Precision	1.000	0.984	1.000	0.996	1.000	1.000
F1	0.991	0.989	0.995	0.985	1.000	0.995
Specificity	1.000	1.000	0.985	0.998	1.000	1.000
AUC-ROC	0.999	0.999	0.986	0.996	1.000	0.997

Figure 7 implies the model correctly classified all test datasets. The use of both feature selection, SMOTE-Tomek balancing, and normalization did not degrade model performance generalization. Rather, it focuses on critical feats for model construction to successfully detect the risk-level predictors with minimal errors (Ojugo & Eboka, 2018b) as in the confusion matrix of Figure 10.

86	0
1	167

Figure 10. Confusion Matrix

4.2. Ablation Studies with Benchmark Comparison

Table 4 shows ablation report with performance of the base learners applied. Our hybrid ensemble yielded best result with F1 0.699, accuracy 0.697, precision and recall values of 0.685 and 0.684 respectively. Conversely, our benchmarks yield the F1 range [0.611, 0.639], Accuracy range [0.619, 0.637], precision range [0.632, 0.64] and recall range [0.634, 0.64] respectively (Malasowe, Okpako, et al., 2024; Ojugo & Okobah, 2018).

Table 5. Comparison with Related Works

Metrics	ACO + BiGRU (Manickam et al., 2022)	BiGRU + FSOR (Luz et al., 2023)	XGB + BiLSTM (Ntampakis et al., 2024)	SEM + DBN (Zetterman et al., 2024)	Proposed Model
F1	0.974	0.991	0.985	0.976	0.995
Accuracy	0.969	0.986	0.992	0.973	0.997
AUC-ROC	0.958	0.928	0.987	0.938	0.997
Recall	0.976	0.989	0.989	0.974	0.998
Precision	0.947	1.000	0.992	0.982	1.000

The study affirms that our proposed model proffers great potentials with improved performance generalization, and a classification accuracy of 0.997 (without data leakage) for predicting risk-levels in maternal mortality. Model maintains high sensitivity performance, even with its transfer learning capabilities (Ojugo, Odiakaose, Emordi, Ako, et al., 2023); And the parameter range enables an in-depth analysis of clinical changes throughout pregnancy, making it valuable to assess and manage high-risk pregnancies.

This dataset supports the deployment of predictive models to improve diagnostic accuracy and enhance outcomes during pregnancy. Additionally, the dataset provides valuable insights for public health strategies and policies related to resource allocation and healthcare planning in maternal health management. The knowledge derived from this data contributes not only to more refined clinical practices. It establishes a foundation for future studies in maternal and public health, ultimately supporting safer pregnancy management and improved maternal and child health outcomes.

4. CONCLUSIONS

The increased early risk-level predictors identification at its training and validation with improved accuracy and decreased loss suggest that the proposed model is robust and well-regularized as its success is attributed to the effective fusion of the data balancing cum normalization of classes, the optimized predictors via feature selection mode, and the suited BiGRU model.

These, have revealed Recall 0.998, Accuracy 0.997, Precision 1.000, F1 0.995, Specificity 1.000 and AUC 0.997 respectively. In addition, the proposed model achieved high discriminative capability via statistically fused heuristics mode to successfully mitigate class-imbalance with enhanced evaluation scores. Study advances a lightweight yet effective framework that avoids complex training and validation that results in overfit or over-parameterization, effectively handles larger data complexities; while offering interpretability and high performance.

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