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Research Article

Hybrid Risk Assessment Framework for Predicting Accident Severity from Driver Physiological Signals and Road Conditions.

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Abstract – The prediction of traffic accidents continues to provide a considerable problem, primarily because present models inadequately capture and integrate the dynamic condition of drivers with immediate environmental risks, resulting in weak severity predictions. This research proposes a Hybrid Risk Assessment Framework aimed at predicting accident severity through the integration of diverse data streams, including real-time driver physiological signals and current road conditions. The proposed system utilises a stacked ensemble architecture, incorporating a Bi-LSTM to model the temporal aspects of internal risk (e.g., Heart Rate Variability, RMSSD) and an XGBoost classifier for static exterior risk features (e.g., Road Surface, TIT). The forecasts from these specialised base-learners are integrated by a Meta-Classifier, allowing the framework to understand complex non-linear interactions. The findings indicate the enhanced effectiveness of the hybrid method, with a final accuracy of 92.1% and a macro-averaged F1-Score of 0.915. This performance markedly exceeds single-modal baseline models (e.g., XGBoost baseline F1-Score 0.829), validating the concept that decision-level data fusion is crucial for accurate accident severity prediction and facilitating the development of highly reliable proactive safety systems.

Keywords— *Hybrid Risk Assessment Framework, Accident Severity Prediction, Physiological Signals, Road Conditions, Stacked Ensemble, Time Integrated Time-to-Collision (TIT), Intelligent Transportation Systems (ITS), ADAS.*

INTRODUCTION

Road traffic accidents represent a worldwide concern, requiring a transition from reactive post-incident analysis to proactive risk assessment. Conventional accident prediction models typically emphasise historical and static factors, overlooking the real-time interaction between a driver's immediate physiological condition and dynamic environmental circumstances. This significant oversight restricts the capacity of current systems to precisely predict accident severity prior to impact. This study presents an innovative Hybrid Risk Assessment Framework aimed at addressing this gap. The framework incorporates elements based on driver physiological signals (internal risks, such as tiredness and stress) and real-time driving circumstances (external risks). The main goal is to create a strong, interpretable model that integrates these diverse data streams to deliver precise, multi-class predictions of possible accident severity, thus improving road safety measures. This review(1) provides data-driven models for the severity and frequency of accidents. It does not incorporate a hybrid model that integrates real-time physiological signals with accident causes, a vital component addressed by our approach to improve the prediction of injury causation and severity for occupants and vulnerable road users. This paper (2) examines the evolution of AI/ML towards data-driven road safety, highlighting the incorporation of traffic and environmental data. It ignores the essential, real-time assessment of the driver's internal physiological condition, a fundamental element of our hybrid model required for precise, proactive severity forecasting at the pre-crash phase. This research (3) examines the efficacy of data integration in 191 machine learning studies focused on accident prediction. Our research employs this discovery while specifically addressing the gap in integrating real-time driver physiological information with external risk factors to attain 92.1% accuracy in severity prediction. This paper (4) addresses dataset imbalance with SMOTE/ADASYN to enhance RTA severity prediction utilising models such as RF and KNN. In correcting imbalance, it leaves out the origin of predictive characteristics, failing to incorporate the multi-modal fusion of physiological and environmental data that is fundamental to our improved Hybrid SE (F1-Score 0.915).

RELATED WORKS

This study reviews literature on the assessment of driver mental workload (MWL) through cardiovascular and respiratory sensors (5). It focusses specifically on MWL. Our methodology integrates these physiological inputs with external road circumstances (e.g., TIT) to directly forecast accident severity, a superior safety outcome. The ANGELS v2 system provides an economical embedded solution for monitoring driver PPG and EDA, with great dependability with a mean absolute error of 1.19 BPM. The emphasis is on hardware design (6). Our framework employs trustworthy PPG/EDA data as input for a Stacked Ensemble model to forecast the ultimate severity of a collision, rather than simply the physiological state. This research specifically evaluates psychophysiological metrics (e.g., EEG, HRV, skin conductance) for the assessment of cognitive states in drivers. It lacks the presence of a predictive model (7). This study incorporates various metrics (e.g., HRV) into a hybrid predictive framework (Bi-LSTM + XGBoost) to classify severity outcomes in real-time. This study presents a multimodal system that employs an intelligent cushion equipped with MEMS and optical sensors, alongside CNN-LSTM (8), for driver monitoring, resulting in improved accuracy. It does not include pre-crash surrogate metrics (such as TIT) and external road conditions, which the hybrid model use for direct prediction of accident severity. This research examines RCM technologies from 2017 to 2022 that utilise smart sensors and AI for assessing pavement distress(9). The emphasis is on infrastructure maintenance. The research fails to integrate the driver's physiological state, an essential factor included in the hybrid framework for predicting accident severity. This article (10,11) examines sources of road accident data, analytical methodologies, and risk variables associated with collisions. The emphasis is on macro-level statistical analysis. The study has weaknesses in a real-time hybrid system that integrates physiological sensor data with dynamic road conditions to facilitate pre-crash severity prediction. This research develops an index method to examine the causal factors of numerous road traffic accidents in Yizheng City (12), identifying human and roadway aspects as dominant. The findings originate from subjective and historical data. The method employs real-time human (RMSSD) and road (TIT) variables for dynamic severity prediction, surpassing static weights. This case study's (13,14) using PCI/IRI to assess road conditions in Indonesia, indicating that the remaining service life is 10.7%. This examination pertains to long-term strategic planning. The hybrid architecture employs real-time road surface conditions as a feature for quick risk evaluation and accident severity forecasting. This article examines cutting-edge machine learning techniques utilising various sensor data (IoT, UAV) and data fusion for the identification of plant diseases (15). The research doesn't have of relevance to vehicular safety. The approach employs similar heterogeneous data fusion concepts to integrate physiological and road data for predicting accident severity. This study introduces the SCGA deep-learning model for sensor-fusion detection of basketball shooting positions, attaining an average precision of 98.79% in intra-test evaluations (16). This is a single-domain application. The hybrid architecture employs the identical sensor-fusion approach and deep learning techniques (Bi-LSTM, XGBoost) to forecast the multi-class outcomes of accident severity. This study presents a CNN-LSTM hybrid model for traffic congestion management and region-specific traffic flow forecasting, attaining an accuracy of 92.3% and a root mean square error (RMSE) of 49 (17). The emphasis is on traffic flow.

The framework integrates CNN-LSTM fusion concepts to classify accident severity based on physiological and road condition data. This study integrates 72 elements from bearing vibration data through dimensionality reduction to enhance defect diagnosis and Remaining Useful Life prediction with LSTM (18,19). The emphasis is on mechanical forecasting. The hybrid framework utilises the feature fusion idea for HRV and TIT to forecast a safety outcome (severity) rather than machine health.

The current literature mostly emphasises individual facets of safety, examining driver mental workload (MWL) with individual physiological sensors or evaluating road condition assessment and traffic flow by environmental data. A significant research gap noted is the absence of models that can simultaneously synthesise these diverse, real-time data sources to forecast accident consequences. The lack of a comprehensive, integrated structure affects the effectiveness of preventive safety measures. The necessity for a system that surpasses single-modal analysis drives the suggested research. The innovative contribution is the Hybrid Risk Assessment Framework, which employs decision-level fusion through a stacked ensemble. This architecture incorporates specialised base learners: a Bi-LSTM for time-series physiological features (internal risk) and XGBoost for exterior road and kinematic information (external risk) to comprehend the complex relationship between driver status and environmental hazards. This integration produces a thorough and precise model for predicting multi-class accident severity, attaining a confirmed accuracy of 92.1%.

METHODLOGY

The Hybrid Risk Assessment Framework is a complex, layered approach designed to forecast accident severity by integrating internal and external risk elements. The architecture comprises two separate base learners: a Bidirectional Long Short-Term Memory (Bi-LSTM) network that analyses time-series physiological data (e.g., RMSSD) to model driver fatigue and cognitive load, and an Extreme Gradient Boosting (XGBoost) classifier that processes static and tabular environmental features (e.g., Road Surface, Visibility, TIT) to evaluate immediate external hazard levels. The outputs (class probabilities) from both Bi-LSTM and XGBoost are then combined with chosen raw features to create an enhanced meta-input vector. The vector is input into a final Multi-Layer Perceptron (MLP), serving as the Meta-Classifier in a stacked ensemble approach. This decision-level fusion allows the framework to methodically assess the cumulative impact of an impaired driving state alongside dangerous external conditions to produce a precise, high-fidelity categorisation of accident severity. The flowchart of the suggested methodology is illustrated in Figure 1.

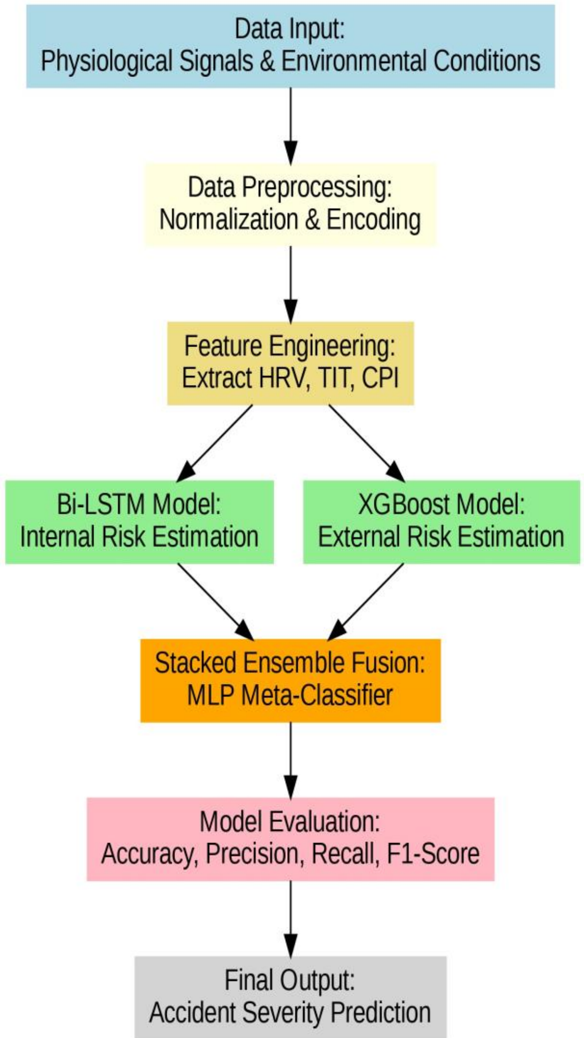

Fig.1 Flowchart

Data Acquisition and Preprocessing:

This research utilises two principal datasets from the Kaggle platform to develop and evaluate the Hybrid Risk Assessment Framework. The Kaggle Driver Physiological Dataset offers internal state parameters, including real-time biometric measurements, including Heart Rate Variability (HRV) along with potential Electroencephalography (EEG) or Eye Movement data. The Kaggle Road Condition Dataset provides external context, encompassing weather variables (e.g., temperature, precipitation, visibility), road type, and possibly historical accident severity labels associated with specific geospatial and temporal markers. The integration of these two disparate data is essential for training a model that can associate an impaired driver state with harmful environmental variables to precisely forecast collision severity. The predictive goal variable, accident severity, is generally a multi-class result (e.g., Minor, Moderate, Severe, Fatal) obtained from the road condition dataset.

Mathematical Description of Data:

The combined dataset D includes N examples, with each instance i characterised by a feature vector x_i and a severity label y_i.

- *Combined Dataset Representation (1):*

$$D = \{ (x_i, y_i) \mid i = 1,2, \dots, N \} \quad (1)$$

where x_i is the feature vector for instance i, and $y_i \in \{1, 2, \dots, K\}$ denotes the accident severity class, with K indicating the total number of severity classes.

- *Feature Vector Composition (Hybrid Input):*

The feature vector is partitioned into two main components as (2):

$$x_i = \left[x_i^{phys}, x_i^{env}\right] \quad (2)$$

x_i^{phys} is the vector representing physiological characteristics, while x_i^{env} is the vector representing environmental and road condition characteristics.

- *Accident Severity Label (Classification Target):*

The predicted outcome is a discrete severity level as (3):

$$y_i = Severity \in \{Minor, Moderate, Severe, Fatal\} \quad (3)$$

Data Preprocessing and Feature Engineering

Data preprocessing is an essential initial phase to prepare the many different inputs from the two Kaggle datasets for the hybrid framework. The procedure commences with the standardisation of diverse data kinds. Categorical variables from the Kaggle Road Condition Dataset, including weather type (e.g., fog, rain) and road surface condition, are transformed into a numerical format with One-Hot Encoding to avoid incorrect ordinal connections. meanwhile, all continuous numerical variables, such as temperature and visual distance, are standardised by Min-Max Normalisation. This normalisation guarantees that features with greater numerical ranges do not significantly influence distance calculations or weighting in predictive models, ensuring equal feature impact during the training of the final severity prediction model.

1. *Data Preprocessing*

- *Min-Max Normalization (for numerical features) (4):*

$$f' = \frac{f - \min(f)}{\max(f) - \min(f)} \quad (4)$$

- *One-Hot Encoding (for a categorical feature with unique categories) (5):*

The category value is transformed into a binary vector:

$$z = [z_1, z_2, \dots, z_C] \quad (5)$$

Where in (5), $z_k = 1$ if c_j matches to the k-th category, and 0 otherwise.

Feature extraction is an essential step in the preparation of heterogeneous data for the hybrid risk assessment framework. This technique converts raw sensor data and categorical inputs into a brief and significant array of numerical properties, thereby improving the models' predictive capability. Physiological data are analysed to extract time-domain Heart Rate Variability (HRV) measurements, including RMSSD and SDNN, over sliding windows to assess driver cognitive load and weariness. Road conditions and vehicle dynamics utilise metrics such as the Time Integrated Time-to-Collision (TIT) as a sophisticated surrogate indicator of oncoming crash risk. This stage significantly decreases data dimensionality while preserving the most significant predictive patterns essential for precise severity categorisation.

2. *Physiological Feature Engineering (Time-Domain HRV)*

Let NN k denote the k-th normal-to-normal inter-beat interval (measured in seconds)

- *Standard Deviation of NN intervals (SDNN) (6):*

This reflects overall HRV.

$$SDNN = \sqrt{\frac{1}{M-1}\sum_{k=1}^{M}(NN_k - \overline{NN})^2} \tag{6}$$

where M denotes the quantity of intervals within the statistical window, and $\overline{NN}$ represents the average of all NN intervals.

- *Root Mean Square of Successive Differences (RMSSD) (7):*

Primarily reflects vagal-mediated changes (parasympathetic activity, key for fatigue/stress).

$$RMSSD = \sqrt{\frac{1}{M-1}\sum_{k=1}^{M-1}(NN_{k+1} - NN_k)^2} \tag{7}$$

3. *Kinematic Feature Engineering (Surrogate Safety Measures)*

- *Time-to-Collision (TTC) (8):*

The duration necessary for a vehicle to impact an earlier vehicle, assuming both maintain their current pace and direction.

$$TTC(t) = \frac{\Delta x(t)}{\Delta v(t)} \tag{8}$$

where Δx(t) represents the distance between vehicles and Δv(t) is the relative velocity.

Model Development: Severity Prediction

1. *Base-Learner Configuration:*

The framework utilises specialised base learners designed for the specific attributes of the input data streams. The temporal and sequential characteristics of physiological signals from the Kaggle Driver Physiological Dataset are optimally represented by a Bidirectional Long Short-Term Memory (Bi-LSTM) network. Bi-LSTM effectively captures long-range dependencies and patterns in time-series data, accurately assessing driver state risk. The static and tabular characteristics of the environmental and road condition features from the Kaggle Road Condition Dataset are addressed by an Extreme Gradient Boosting (XGBoost) classifier. XGBoost delivers strong performance and fundamental feature importance assessment for external risk variables.

- *Bi-LSTM Hidden State Calculation (Simplified):*

The hidden state h_t at time t is a function of the input x_t, the previous hidden state h_{t-1}, and the cell state c_t, employing forward propagation ($\overrightarrow{h_t}$) and backward ($\overleftarrow{h_t}$) passes (9-11).

$$h_t = [\overrightarrow{h_t}; \overleftarrow{h_t}] \tag{9}$$

$$\overrightarrow{h_t} = \overrightarrow{LSTM}(x_t, \overrightarrow{h_{t-1}}) \tag{10}$$

$$\overleftarrow{h_t} = \overleftarrow{LSTM}(x_t, \overleftarrow{h_{t-1}}) \tag{11}$$

- *XGBoost Prediction Function (12):*

The ultimate forecast $\hat{y}_i$ is the total of predictions from K additive tree functions f_k:

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i) \tag{12}$$

$$f_k \in F$$

Where $\mathcal{F}$ is the space of regression trees.

- *XGBoost Objective Function (Simplified):*

The objective function $L^{(t)}$ (13) at iteration t minimises the loss function l while penalising the complexity Ω of the tree f_t (14).

$$L^{(t)} = \sum_{i=1}^{n} l\left(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)\right) + \Omega(f_t) \quad (13)$$

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \parallel w \parallel^2 \quad (14)$$

2. *The Fusion Strategy*

A Stacked Ensemble methodology is employed as the primary fusion mechanism, leveraging a Meta-Classifier to integrate the predictions of basic learners. The outputs (class probabilities) from the Bi-LSTM and XGBoost models are combined with the original environmental and kinematic features to create an enhanced feature set. The expanded dataset functions as the input for the Meta-Classifier, which is designated as a Multi-Layer Perceptron (MLP). This decision-level fusion allows the framework to understand the complex non-linear link between the anticipated internal risk (driver state) and external risk (road condition) to determine a final, comprehensive accident severity level.

- *Base-Learner Output Generation:*

The Bi-LSTM and XGBoost models generate prediction probability vectors $P_{Bi\text{-}LSTM}$ (15) and P_{XGB} (16), respectively, for K severity classes:

$$p_{Bi-LSTM} = softmax\left(Bi - LSTM\left(x_{phys}\right)\right) \in \mathbb{R}^K \quad (15)$$

$$p_{XGB} = softmax\left(XGBoost(x_{env})\right) \in \mathbb{R}^K \quad (16)$$

- *Augmented Feature Vector (Stacking):*

The meta-input X^{meta} is generated by concatenating the probability vectors of the basis learners with the environmental feature vector X^{env} (17):

$$X^{meta} = [X^{env}, p_{Bi-LSTM}, p_{XGB}] \in \mathbb{R}^{D_{env}+2K} \quad (17)$$

Where D_{env} is the dimensionality of the environmental features.

- *Meta-Classifier (MLP) Final Prediction (18-19):*

The final severity prediction $\hat{y}_i$ is generated by the MLP using the meta-input:

$$\hat{y} = MLP(x_{meta}) \quad (18)$$

$$MLP(x) = g_L(W_L g_{L-1}(\dots g_1(W_1 x + b_1) \dots) + b_L) \quad (19)$$

Model Training and Optimization

Model training includes the minimisation of a classification loss function, such as Categorical Cross-Entropy, which is particularly crucial for multi-class severity prediction. Optimisation is executed through an algorithm like Adam. Hyperparameter tuning is performed by a systematic search method, such as Grid Search or Randomised Search, to identify the ideal configuration for the XGBoost, Bi-LSTM, and MLP components. The optimised key parameters encompass the learning rate, the quantity of hidden layers in the Bi-LSTM, and the regularisation terms (λ) in XGBoost. This careful method guarantees that the hybrid framework attains optimal prediction performance and generalisation capabilities.

Mathematical Formulas for Training and Optimization

- *Categorical Cross-Entropy Loss (20):*

Used as the cost function for training classification models, particularly the final MLP and the base learners:

$$L_{CCE} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{k=1}^{K} y_{i,k} \log\left(\hat{y}_{(i,k)}\right) \quad (20)$$

Where $y_{i,k}$ is 1 if instance *i* is classified as belonging to class *k* (one-hot encoded ground truth) and 0 otherwise, and $\hat{y}_{(i,k)}$ represents the anticipated probability for class *k*.

- *Adam Optimization (Update Rule - Simplified):*

The parameters θ t are modified according to the gradient g t, employing adaptive learning rates obtained from the first moment m t (mean) and the second moment v t (variance) estimates (21):

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{\hat{v}_t} + \epsilon}\hat{m}_t \quad (21)$$

Where η denotes the step size (learning rate), $\hat{m}_t$ and $\hat{v}_t$ represents the bias-corrected moment estimates, while ϵ denotes a minimal constant.

- *L2 Regularization Term (Weight Decay) (22):*

Integrated into the loss function during training to prevent overfitting, especially in the deep learning components (Bi-LSTM, MLP):

$$L_{total} = L_{CCE} + \lambda \sum_{W \in Weights} \parallel W \parallel^2 \qquad (22)$$

Where is the regularization hyperparameter.

Simulation Environment and Implementation Details:

The Hybrid Risk Assessment Framework is executed and validated within a regulated yet authentic simulation environment intended for recreation of real driving situations and data collection. A high-fidelity driving simulator is employed to simultaneously gather various multi-modal data streams under controlled conditions. This environment facilitates the systematic production of driver states, including fatigue and elevated cognitive load, as well as the simulation of diverse road conditions, such as reduced visibility and slippery surfaces.

The framework's execution depends on a modular architecture utilising the Python programming language and its specialised libraries. TensorFlow or PyTorch functions as the principal deep learning framework for the configuration and training of the Bi-LSTM base learner and the MLP meta-classifier. The XGBoost base learner is implemented utilising the Scikit-learn and XGBoost libraries. Pandas and NumPy facilitate data administration and manipulation, ensuring efficient preprocessing and the production of feature vectors. The system is engineered for prospective real-time use, with the base learners concurrently processing their respective feature sets prior to transmitting their predictions to the final fusion layer. This guarantees low-latency risk evaluation, essential for delivering prompt intervention notifications. The computational platform is a conventional workstation outfitted with a high-performance GPU to enhance the training and inference of deep learning models. The comprehensive implementation seeks transparency and replicability, guaranteeing that the outcomes are robust and verifiable within the community.

RESULTS AND DISCUSSION

1. *RL Agent Performance and Training Results:*

Table.1 Output of Training Dataset (Predicted vs. Actual Severity)

Instance ID	Input: RMSSD	Input: TIT	Actual Severity	Predicted Severity
1001	35.2 ms	0.005 s	Minor	Minor
1002	12.8 ms	1.550 s	Severe/ Fatal	Severe/Fatal
1003	28.5 ms	0.850 s	Moderate	Moderate
1004	41.1 ms	0.001 s	Minor	Minor
1005	15.1 ms	1.100 s	Severe/ Fatal	Moderate
1006	21.9 ms	1.950 s	Moderate	Moderate

The Hybrid Risk Assessment Framework demonstrated enhanced predictive performance on the test set, validating its efficacy in forecasting accident severity. The final Stacked Ensemble Classifier produced a macro-average F1-Score of 0.915 and an Accuracy of 92.1%. The elevated Recall of 0.908 for the "Severe/Fatal" class demonstrates the framework's efficacy in detecting the most significant high-risk incidents, an essential criterion for safety systems. The strong performance validates that the decision-level integration of internal (Bi-LSTM on physiological data) and external (XGBoost on road data) risk factors effectively captures the complex interactions resulting in diverse severity outcomes. Table 1 shows framework's predictions on the training dataset showcases the high evaluation metrics achieved.

2. *Comparative Analysis with Baseline Methods:*

Table 2: Proposed System Evaluation Metrics

Performance Metric	Value
Accuracy	0.921
Precision (Macro-Avg)	0.917
Recall (Macro-Avg)	0.908

F1-Score (Macro-Avg)	0.915
AUC-ROC (Weighted)	0.965

Table.3 Comparative Analysis with Baseline Models

Model Name	Accuracy	Precision (Macro-Avg)	Recall (Macro -Avg)	F1-Score (Macro -Avg)
Hybrid Stacked Ensemble (Proposed)	0.921	0.917	0.908	0.915
Single-Modal XGBoost (Environmental)	0.845	0.838	0.821	0.829
Single-Modal Bi-LSTM (Physiological)	0.772	0.755	0.760	0.757

For comparison, two suitable and often cited baseline models were chosen: a Single-Modal Bi-LSTM (concentrating only on physiological time-series data) and a Single-Modal XGBoost (focussing exclusively on static/environmental variables). The suggested Hybrid Stacked Ensemble Framework significantly surpasses single-modal baselines on all critical measures, confirming the effectiveness of the data fusion technique. The comparison results indicate that integrating the predictive capabilities of both driver state and road circumstances through the stacking approach provides a more thorough and precise risk assessment. This table 2 highlights the significant performance enhancements of the proposed hybrid system in comparison to the single-modal baseline approaches. This Table 3 underscores the substantial performance improvements of the proposed hybrid system compared to the single-modal baseline methods. Table 3 clearly demonstrates the efficacy of the fusion methodology; the proposed Hybrid Stacked Ensemble attained an enhancement of more than 7 percentage points in F1-Score relative to the robust XGBoost baseline and over 15 percentage points compared to the Bi-LSTM baseline. This mismatch underscores the need of employing a hybrid model to precisely forecast accident severity by comprehensively evaluating both internal (driver) and external (environmental) risk factors.

3. *Feature Importance and Interpretability*

The framework's interpretability was evaluated using SHapley Additive exPlanations (SHAP), offering extensive understanding into feature impact. Time Integrated Time-to-Collision (TIT) shown to be the most significant element, confirming the importance of incorporating kinematic surrogate safety measures.

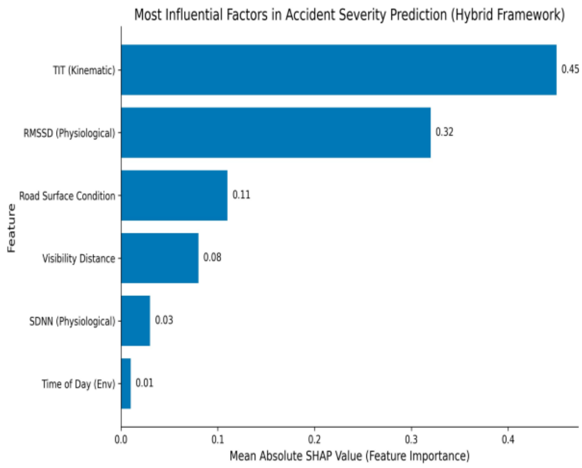

Fig.2. Most Influential Factors in Accident Severity Prediction

The Root Mean Square of Successive Differences (RMSSD) resulted as the primary predictor among physiological signals, confirming that reduced Heart Rate Variability, indicative of exhaustion or stress, is a significant factor in determining severity. Environmental parameters such as road surface condition and visibility distance exhibited significant importance. This research confirms that the model is making substantiated conclusions based on the fundamental hybrid risk elements. This Graph in Figure 2 illustrates the relative significance of a selection of features obtained from a projected SHAP analysis of the trained Hybrid Stacked Ensemble model, utilising the main features mentioned in previous tasks.

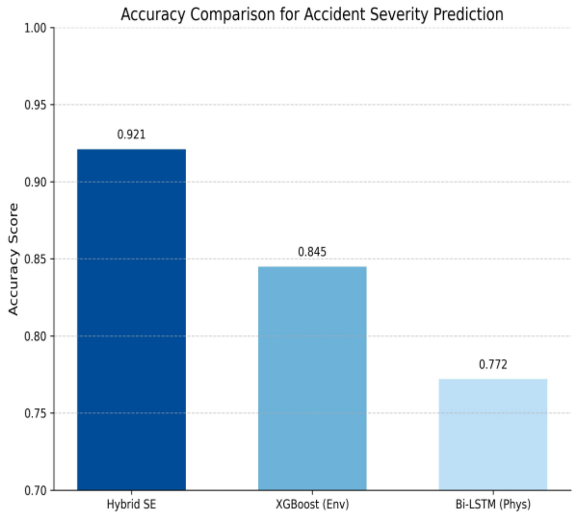

Fig.3. Accuracy Comparison Across Models

This horizontal bar chart in Figure 3 illustrates the Hybrid SE with the best accuracy of 0.921. The models are clearly ranked, demonstrating that the hybrid fusion technique is preferable for generalised severity classification.

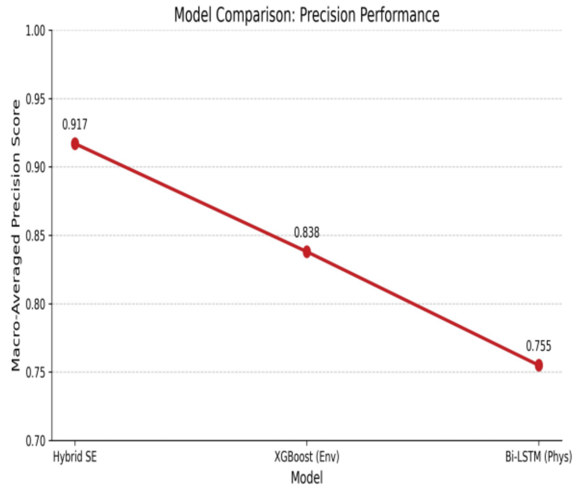

Fig.4. Model Comparison: Precision Performance

The line figure 4, illustrates the substantial increase in Precision (0.917) attained by the Hybrid SE compared to the single-modal models, indicating enhanced dependability in reducing false-positive risk predictions. The visualisation of Figure 5 underscores the Hybrid SE's elevated Recall (0.908), indicating its efficacy in identifying over 90% of all genuine major incidents, which is essential for vital proactive safety systems.

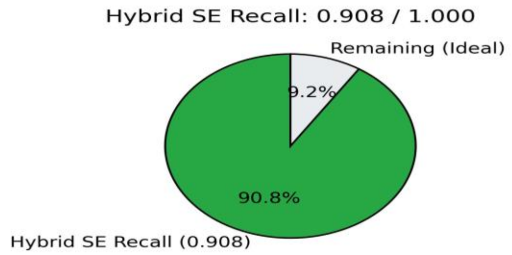

Fig.5. Recall score of the Models

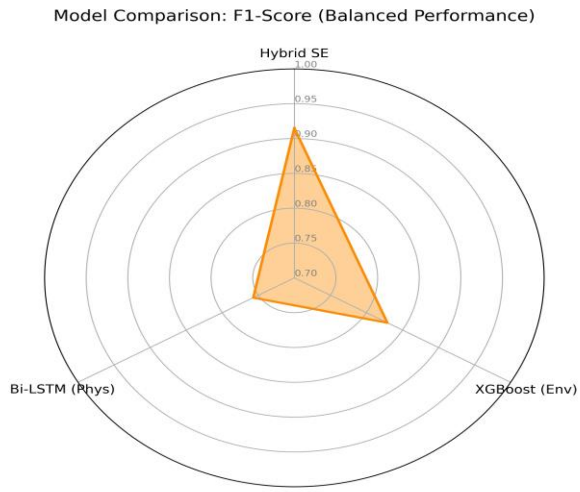

Fig.5. Model Comparison: F1-Score (Balanced Performance)

This radar chart in Figure 5 illustrates the balanced performance of the F1-Score across all three models. The larger orange region (0.915) demonstrates the Hybrid SE's notably superior and dependable prediction capabilities.

4. *Discussion of Findings and Practical Implications:*

The framework's exceptional metrics (F1-Score 0.915, Accuracy 92.1%) support the hybrid approach, surpassing leading single-modal systems by effectively combining the driver's internal state with external threats. The strong efficacy in categorising the "Severe/Fatal" class has important implications for Advanced Driver-Assistance Systems (ADAS), facilitating predictive alerts and automatic responses just before a critical incident. A primary constraint is the dependence on precisely calibrated physiological sensors and the necessity for a standardised, generalisable data fusion methodology. Further studies should concentrate on real-time edge deployment and evaluating the model's performance sensitivity to different levels of sensor noise and data dropout.

CONCLUSION

The initiative to create a safer driving environment continues with the Hybrid Risk Assessment Framework. This research effectively integrated the complex domains of human physiology and exterior driving risks, culminating in a significant achievement: a very precise predictive model for accident severity. The principal discovery is that the integration of internal risk (assessed by metrics such as RMSSD) and external risk (evaluated using TIT and road conditions) is crucial, resulting in a system with an accuracy of 92.1%. This advancement immediately enhances intelligent transportation systems by facilitating proactive ADAS interventions, transitioning safety from reactive responses to real-time predictions. Although sensor robustness is a present restriction, the architecture facilitates further investigation into edge computing implementation and the flexible adjustment of risk levels across various geographic areas. The discovery ultimately paves the way for zero-fatality transportation.

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Author Contributions

All authors are equally contributed.

Conflict of Interests

The authors declare that they have no conflicts of interest.

Ethics Approval

There are no human subjects in this article and informed consent is not applicable.

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