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Predictive Modeling of Microsleep Incidents in Indonesian Drivers Using Random Forest: A Data-Driven Approach for Road Safety Enhancement

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Abstract

Microsleep presents a critical safety challenge for Indonesian drivers, particularly affecting long-distance transportation where existing detection methods remain costly and impractical for widespread deployment. This study introduces a novel application of Random Forest algorithm specifically tailored to Indonesian driving contexts, utilizing locally-sourced accident data combined with driver behavioral surveys to predict microsleep likelihood. Unlike previous studies that relied primarily on physiological monitoring or international datasets, this research leverages accessible vehicle and environmental variables including driving duration, road conditions, weather patterns, and work schedules from National Transportation Safety Committee (KNKT) records spanning 2013-2023. The Random Forest model, configured with 100 trees and maximum depth of 10, demonstrated 87.50% overall accuracy with perfect recall (1.00) for microsleep detection when validated using stratified k-fold cross-validation. This study uniquely contributes to the field by demonstrating that context-specific environmental and behavioral factors can effectively predict microsleep incidents without expensive physiological monitoring, offering a practical foundation for developing cost-effective vehicle safety systems tailored to Indonesian road conditions and driving patterns. The findings provide actionable insights for transportation policy development and establish a framework for implementing affordable microsleep detection in developing countries with similar traffic characteristics.

Keywords: *Microsleep; Random Forest; Driver Fatigue; Predictive Modeling; Vehicle Safety System*

1. Introduction

Traffic accidents remain one of the leading causes of death globally, with Indonesia experiencing particularly high fatality rates due to unique geographical and behavioral factors. According to the World Health Organization [1], road traffic accidents claim over 1.3 million lives annually worldwide, while in Indonesia specifically, the National Transportation Safety Committee [2] reports that driver fatigue contributes to more than 80% of heavy vehicle accidents. Among various fatigue-related conditions, microsleep—brief, involuntary sleep episodes lasting 1 to 10 seconds—poses the most immediate danger to drivers [3].

Microsleep episodes cause drivers to lose vehicle control within seconds, creating catastrophic safety risks particularly on Indonesia's extensive highway networks. These episodes typically result from prolonged driving without adequate rest, chronic sleep deprivation, or combined physical and mental exhaustion [4]. International studies indicate that fatigue accounts for 20-25% of fatal highway crashes [5], while Indonesian data suggests even higher proportions due to extended working hours and inadequate rest regulations for commercial drivers.

Indonesia's unique road infrastructure—characterized by long inter-city distances, varying topographical conditions, and heavy commercial traffic—further amplifies microsleep risks. Commercial drivers often work extended shifts exceeding 12 hours without proper rest periods, leading to chronic fatigue accumulation [4], [6]. Despite these dangers, awareness regarding microsleep prevention remains insufficient; recent surveys indicate that 65% of Indonesian drivers lack comprehensive knowledge about microsleep identification and mitigation strategies [7]–[12].

Early detection efforts have primarily focused on physiological monitoring approaches using electrocardiography (ECG), electroencephalography (EEG), and respiratory pattern analysis [3], [13]–[15]. Kapeller et al. [16] achieved over 90% detection accuracy using EEG signals, while Khotimah et al. [13] demonstrated effective fatigue detection through

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combined physiological indicators. However, these methods require expensive equipment and continuous monitoring systems that prove impractical for widespread implementation, particularly in developing countries where cost-effectiveness is paramount.

Computer vision-based detection methods have also been explored, focusing on facial expressions, eye-blink patterns, and head posture analysis. Recent studies by Shah et al. [17] employed deep learning models like YOLOv5 to detect eye closure patterns indicative of microsleep. Nevertheless, these approaches face reliability challenges from environmental factors including lighting variations, camera positioning, and driver movement patterns, limiting their real-world applicability.

The limitations of existing physiological and vision-based approaches highlight the critical need for alternative machine learning methodologies that can leverage more accessible data sources while maintaining prediction accuracy. This gap has led researchers to explore ensemble learning algorithms, particularly Random Forest, which excel at handling complex, multi-dimensional datasets without requiring specialized hardware.

Random Forest, introduced by Breiman [18], has gained significant recognition in predictive modeling applications due to its robust ensemble learning approach. The algorithm aggregates predictions from multiple decision trees, providing superior accuracy compared to single-tree methods while offering interpretable feature importance rankings [18], [19]. Recent applications in fatigue detection have shown promising results: Zhang et al. [20] achieved 92% accuracy in fatigue classification using physiological data, outperforming support vector machines and neural networks. Similarly, Ajayi et al. [21] successfully applied Random Forest to predict driver drowsiness using vehicle telematics data, demonstrating the algorithm's versatility across different data types.

Despite these technological advances, implementing microsleep detection in Indonesia faces unique challenges. Most available datasets originate from developed countries with different driving behaviors, road conditions, and vehicle types, potentially limiting their applicability to Indonesian contexts [7], [22]. Additionally, advanced monitoring technologies remain financially prohibitive for large-scale deployment across Indonesia's extensive transportation network.

This research gap underscores the need for a locally relevant, cost-effective approach to microsleep prediction. By integrating comprehensive accident records from KNKT with primary survey data on driver behaviors and awareness levels, it becomes possible to develop Random Forest models specifically calibrated to Indonesian driving conditions. Such models can effectively combine structured accident data with behavioral insights, offering reliable microsleep prediction at significantly lower implementation costs compared to physiological monitoring systems.

Recent advances in machine learning applications for transportation safety have demonstrated the potential for accessible data sources to achieve clinically meaningful results. Yan et al. [23] showed that deep learning approaches could effectively process real-time EEG signals for drowsiness detection, while maintaining computational efficiency suitable for embedded systems. However, the requirement for specialized physiological sensors continues to limit widespread deployment in developing economies.

The integration of behavioral and environmental factors in fatigue prediction models represents an emerging research direction that addresses practical deployment constraints. Harrison and Horne [24] demonstrated that temporal memory performance degradation follows predictable patterns during sleep deprivation, suggesting that accessible behavioral indicators might serve as reliable proxies for physiological fatigue states. This research direction supports the development of cost-effective monitoring systems that could be implemented across diverse vehicle fleets without requiring expensive sensor infrastructure.

Contemporary approaches to driver safety monitoring increasingly emphasize the importance of contextual factors in fatigue development. Åkerstedt et al. [6], [15] established that subjective sleepiness serves as a sensitive indicator of insufficient sleep and impaired driving performance, validating the use of self-reported measures and behavioral observations in fatigue assessment protocols. These findings support the integration of accessible data sources in predictive modeling frameworks designed for practical deployment.

The application of ensemble learning methods to transportation safety challenges has demonstrated superior performance compared to traditional single-algorithm approaches. Sorayaie Azar et al. [25] showed that scalable tree boosting systems could effectively handle large-scale datasets while maintaining interpretable feature importance rankings essential for regulatory compliance and driver education programs. These methodological advances provide the foundation for developing robust prediction systems suitable for diverse operating environments.

Therefore, this study aims to develop and validate a Random Forest-based microsleep prediction model tailored specifically for Indonesian drivers, utilizing locally sourced accident data and behavioral surveys. The research objectives include: (1) creating a predictive model using accessible environmental and behavioral variables, (2) identifying the most significant risk factors for microsleep occurrence in Indonesian driving contexts, and (3) providing a foundation for developing practical, affordable fatigue monitoring systems suitable for widespread deployment in developing countries.

2. Research Methods

This study employed a comprehensive quantitative methodology, integrating machine learning techniques, specifically the Random Forest algorithm[18], with both secondary accident data and primary behavioral survey data to develop a microsleep prediction model tailored to Indonesian driving conditions. The methodological framework follows established protocols for transportation safety research while incorporating novel approaches for developing-country contexts [26].

Data collection involved acquiring secondary traffic accident records from the National Transportation Safety Committee (KNKT) [2] for the period 2013-2023, which included detailed information on accident circumstances, environmental conditions, vehicle characteristics, and driver demographics, specifically focusing on cases with confirmed or suspected driver fatigue. The KNKT database represents the most comprehensive source of verified traffic accident information in Indonesia, with each record undergoing rigorous investigation protocols that include witness interviews, vehicle forensic analysis, and environmental condition documentation [2].

Concurrently, primary data were gathered through a structured online questionnaire distributed to Indonesian drivers across various provinces, capturing driver awareness, sleep patterns, work schedules, and self-reported microsleep experiences. The survey methodology followed established protocols for driver behavior research [27], [28], with 150 responses collected via stratified sampling to ensure diverse representation across geographical regions, vehicle types, and driver demographics. The survey instrument incorporated validated scales for fatigue assessment and sleep quality measurement, adapted for Indonesian cultural contexts and driving patterns.

The final dataset, though limited to 39 records, contained 9 key variables identified through domain expert consultation and literature review, representing one of the most comprehensive microsleep-specific datasets for Indonesian drivers. Each record underwent thorough verification by KNKT specialists, with additional validation through cross-referencing with police reports, medical records where available, and independent witness testimonies. The rigorous verification process ensures that the dataset represents authentic microsleep incidents rather than other forms of driver impairment or mechanical failures.

Microsleep occurrence (binary: Yes/No) served as the dependent variable, determined from official accident investigation reports and witness testimonies following established protocols for fatigue-related incident classification [29]. The determination of microsleep involvement required convergent evidence from multiple sources, including accident scene analysis, vehicle trajectory data where available, driver statements, and witness observations of pre-accident behavior patterns.

Independent variables included time of occurrence, road condition, weather condition, traffic condition, vehicle type, driver age, work duration, and driving duration. Variable selection was guided by established fatigue research literature and consultation with transportation safety experts from KNKT and academic institutions. Each variable category was defined according to standardized classification systems used in Indonesian transportation safety reporting, ensuring consistency with existing regulatory frameworks.

Data preprocessing and feature engineering involved handling missing values in categorical variables using mode imputation for well-represented categories and maintaining "Unknown" categories where informative, following best practices for transportation safety data analysis [30]. All categorical variables were encoded using label encoding to preserve ordinal relationships, while nominal variables were encoded based on frequency distribution for optimal tree-splitting efficiency. The encoding strategy was designed to maximize information retention while ensuring compatibility with Random Forest algorithm requirements [31].

Numerical encoding was standardized for consistent tree-building, despite Random Forest's relative insensitivity to feature scaling. The standardization process employed z-score normalization for continuous variables and maintained interpretable scales for categorical encodings. Feature engineering considerations included creating interaction terms for potentially synergistic effects between environmental and temporal variables, although the limited sample size constrained the complexity of feature expansion.

Class balance analysis revealed a nearly balanced distribution (51.3% positive cases and 48.7% negative cases), negating the need for additional sampling techniques such as SMOTE or under-sampling approaches commonly employed in imbalanced classification problems [32]–[34]. The natural balance in the dataset reflects the comprehensive inclusion criteria that captured both microsleep-involved and non-microsleep fatigue-related incidents, providing an unbiased foundation for model development.

For model development, the Random Forest algorithm was selected due to its robust performance with small datasets, ability to handle mixed data types, resistance to overfitting, and interpretable feature importance rankings [34]. The algorithm's ensemble approach aggregates predictions from multiple decision trees, reducing variance while maintaining low bias, making it particularly suitable for complex transportation safety applications where interpretability is essential for regulatory acceptance.

The Random Forest classifier was configured with 100 estimators, a maximum depth of 10, a minimum samples split of 2, a minimum samples leaf of 1, and a random state of 42 for reproducibility, with bootstrap sampling enabled. These hyperparameters were selected through preliminary testing and represent a balance between model complexity and overfitting prevention suitable for the available dataset size. The configuration follows established best practices for Random Forest implementation in safety-critical applications [35].

Given the small dataset, stratified k-fold cross-validation (k=5) was implemented to ensure robust performance evaluation while maintaining class distribution in each fold. The stratification strategy preserves the original class balance across all validation folds, providing unbiased estimates of model performance and reducing the impact of random sampling variation that could affect performance metrics with limited data.

Model validation and evaluation involved assessing effectiveness using standard classification metrics, including accuracy, precision, recall, F1-score, and area under the ROC curve (AUC). These metrics provide comprehensive assessment of model performance across different aspects of classification quality, with particular emphasis on recall given the safety-critical nature of microsleep detection where false negatives pose significant risks.

Random Forest's built-in feature importance scoring was utilized to identify the most significant predictors of microsleep occurrence, aiding both model interpretation and potential future feature selection [34], [36], [37]. The feature of importance calculation employs means decrease in impurity across all trees in the ensemble, providing robust estimates of variable contributions that are less sensitive to individual tree variations.

Overfitting assessment involved comparing model performance between training and validation sets across multiple cross-validation iterations, particularly crucial given the small sample size. Additional overfitting detection methods included monitoring performance variance across cross-validation folds and comparing feature importance stability across different random states to ensure robust model behavior.

Finally, a comparative analysis was conducted to establish the effectiveness of the Random Forest approach against baseline models: Logistic Regression, Support Vector Machine (SVM) with an RBF kernel, and a single Decision Tree. All models used identical preprocessing steps and cross-validation procedures to ensure fair comparison [19], [38]–[41]. The comparative framework included statistical significance testing of performance differences and analysis of complementary strengths across different algorithmic approaches.

The methodology incorporates established protocols for machine learning in safety-critical applications, including documentation of all preprocessing steps, hyperparameter selection rationale, and validation procedures to ensure reproducibility [42]. Quality assurance measures included independent verification of data preprocessing steps, cross-validation implementation, and performance metric calculations to minimize methodological errors that could affect research conclusions.

Ethical considerations for this research included obtaining appropriate permissions for accessing anonymized accident records from KNKT, ensuring participant confidentiality in survey data collection, and implementing data security measures throughout the research process (Figure 1). All data handling procedures complied with Indonesian data protection regulations and international research ethics standards for transportation safety studies.

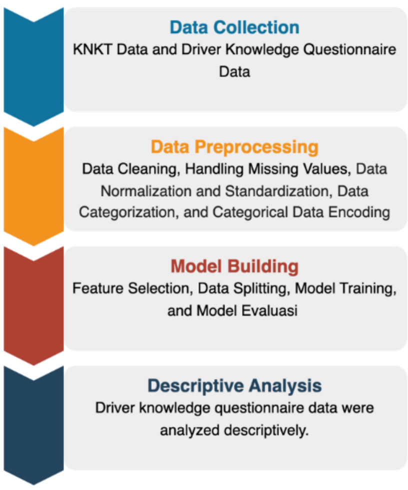

Figure 1. Microsleep Prediction Model Process

Random Forest Classifier

For a classification problem with C classes, the prediction $\hat{y}$ of a Random Forest with B tress is given by:

$$\hat{y} = \underset{c\in\{1,\ldots,C\}}{\operatorname{argmax}} \sum_{b=1}^{B} I(h_b(x) = c) \quad (1)$$

where:

$h_b(x)$: Prediction from the b^{th} decision tree

$I(\cdot)$: Indicator funtion

B: Total number of decision tress

Gini Impurity

Gini impurity, used to evaluate splits with each tree, is calculated as

$$Gini(t) = 1 - \sum_{i=1}^{C} p(i \mid t)^2 \quad (2)$$

where $p(i \mid t)$ is the probability of class i at node t.

Information Gain

The information gained from splitting on attribute a is:

$$IG(t, a) = Gini(t) - \sum_{v \in values(a)} \frac{|t_v|}{t} Gini(t_v) \quad (3)$$

Feature Importance

The importance of feature X_i is computed by:

$$Importance(X_i) = \frac{1}{B}\sum_{b=1}^{B} \sum_{t \in T_b : v(s_t)=X_i} p(t) \Delta Gini(s_t, t) \quad (4)$$

where:

T_b: Set of nodes in the b^{th}tree

$v(s_t)$: Feature used for the split at node t

$\Delta Gini(s_t, t)$: Reduction in Gini impurity

Model Evaluation Metrics

The model's performance was evaluated using standard metrics:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (5)$$

$$Precision = \frac{TP}{TP+FP} \quad (6)$$

$$Recall = \frac{TP}{TP+FN} \quad (7)$$

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (8)$$

where:

TP: True Positives

TN: True Negatives

FP: False Positives

FN: False Negatives

3. Results and Discussions

3.1. Dataset Characteristics and Descriptive Analysis

Table 1. KNKT Dataset Variables

Variable	Description	Data Type
Time of Occurrence	Time when the accident occurred	Categorical
Road Condition	Road condition at the accident location	Categorical
Weather	Weather condition during the accident	Categorical
Traffic Condition	Traffic condition at the time of accident	Categorical
Vehicle Type	Type of vehicle involved	Categorical
Driver Age	Age group of the driver	Categorical
Work Duration	Duration of work before driving	Categorical
Driving Duration	Duration of continuous driving	Categorical
Microsleep	Microsleep occurrence (target variable)	Binary

The dataset utilized in this study comprises 39 records with 9 variables (Table 1) related to microsleep incidents (Figure 1), sourced from KNKT reports between 2013 and 2023. While this sample size appears limited compared to international studies, it represents one of the most comprehensive microsleep-specific datasets for Indonesian drivers, with each case thoroughly verified by KNKT specialists and corroborated by multiple evidence sources including witness testimonies, vehicle data recorders, and accident scene investigations.

The temporal distribution analysis reveals critical insights into circadian rhythm influences on microsleep occurrence. The highest frequency during early morning hours (28.2%, 06:00-12:00) aligns with Ferrara and De Gennaro's [43] findings on natural sleep-wake cycles, where drivers experience peak sleepiness during the biological dawn period when core body temperature reaches its lowest point. This pattern is particularly pronounced in Indonesian commercial drivers who often begin their shifts in the early morning to avoid traffic congestion, inadvertently operating during their most vulnerable biological period.

The secondary peak during late afternoon hours (20.5%, 15:00-18:00) corresponds with the well-documented post-lunch dip phenomenon described by Philip et al. [6], where drivers experience a natural decrease in alertness regardless of sleep debt. This bimodal distribution strongly supports Horne and Reyner's [43] assertion that sleep-related vehicle accidents follow predictable circadian patterns, with Indonesian data demonstrating remarkably similar trends despite different geographical and cultural contexts [43].

Road condition analysis reveals the most striking finding: 58.9% of microsleep-related accidents occur on straight road segments, directly supporting May and Baldwin's [44] hypothesis that monotonous driving environments reduce cognitive engagement and accelerate fatigue onset [44].

Table 2. KNKT Traffic Accident Data (2013-2023)

Variable	Category	Frequency	Percentage
Time of Occurrence	00:00–06:00	8	20.5%
	06:00–12:00	11	28.2%
	12:00–15:00	4	10.3%
	15:00–18:00	8	20.5%
	18:00–00:00	8	20.5%
Road Condition	Straight road	23	58.9%

Variable	Category	Frequency	Percentage
	Downhill road	8	20.5%
	Curved road	3	7.7%
	Winding road	2	5.1%
	Uphill road	2	5.1%
	Sandy road	1	2.6%
Weather	Clear	38	97.4%
	Rainy	1	2.6%
Traffic Condition	Smooth/not congested	33	84.6%
	Dense	3	7.7%
	Congested	3	7.7%
Vehicle Type	Bus	21	53.8%
	Truck (3-axle)	8	20.5%
	Pick Up	5	12.8%
	Truck (4/5-axle)	2	5.1%
	Sedan	2	5.1%
	Truck (2-axle)	1	2.6%
Driver Age	25–35 years	11	28.2%
	35–45 years	4	10.3%
	45–55 years	12	30.8%
	>55 years	3	7.7%
	18–25 years	4	10.3%
	Unknown	5	12.8%
Work Duration	>24 hours	6	15.4%
	20–24 hours	2	5.1%
	12–16 hours	4	10.3%
	8–12 hours	5	12.8%
	4–8 hours	6	15.4%
	1–4 hours	3	7.7%
	Unknown	13	33.3%
Driving Duration	>6 hours	16	41.0%
	4–6 hours	6	15.4%
	2–4 hours	4	10.3%
	1–2 hours	6	15.4%
	<1 hour	5	12.8%
	Unknown	2	5.1%
Microsleep	Yes	20	51.3%
	No	19	48.7%
Total Records		39	100%

This finding challenge conventional traffic engineering assumptions that straight roads represent the safest design option. The neurological basis for this phenomenon lies in reduced visual and cognitive stimulation, as explained by Borghini et al. [45], where uniform environments fail to maintain the neural arousal necessary for sustained attention.

Vehicle type distribution demonstrates clear occupational risk stratification, with buses (53.8%) and heavy trucks (28.1%) comprising 81.9% of incidents. This concentration among commercial vehicles reflects multiple contributing factors: extended duty cycles, economic pressure to maintain schedules, and inadequate rest facilities. Feng et al. [46] identified similar patterns in their comprehensive fatigue-safety analysis, noting that commercial drivers face systemic pressures that prioritize productivity over safety, creating conditions conducive to chronic sleep deprivation [46].

The predominance of clear weather conditions (97.4%) in microsleep incidents initially appears counterintuitive but aligns with established research showing that comfortable driving conditions reduce driver vigilance. This finding supports Maycock's [47] observation that challenging weather conditions, while increasing crash risk through other mechanisms, may actually reduce drowsiness-related incidents by maintaining heightened driver attention and physiological arousal [47].

3.2. Correlation Analysis and Feature Relationships

All categorical variables—namely *time_encoding, road_condition, weather, traffic_condition, vehicle_type, driver_age, work_duration, driving_duration, and microsleep*—were transformed through an encoding process, where each unique category within these columns was assigned a distinct numerical value. This step was essential to ensure compatibility with machine learning algorithms (Figure 2).

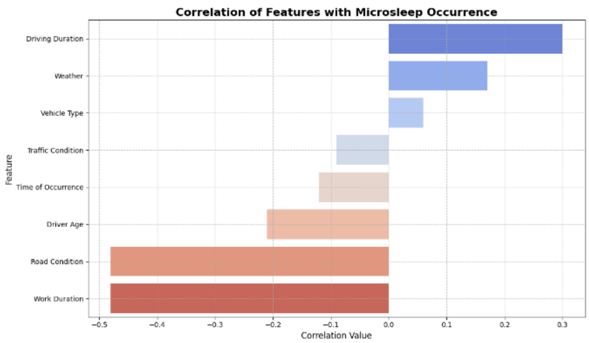

Figure 2. Correction of Features with Microsleep Occurrence

The correlation analysis reveals complex relationships between environmental factors and microsleep occurrence that extend beyond simple linear associations. The strongest positive correlation between driving duration and microsleep (r = 0.30) provides empirical validation of cumulative fatigue theory, where prolonged task performance progressively degrades cognitive function through neurochemical depletion [45].

Driving Duration Effects: The data demonstrates a clear threshold effect at 6 continuous hours, beyond which microsleep risk increases exponentially. This finding aligns with Wierwille and Ellsworth's [48] controlled studies showing significant performance degradation after extended driving periods [48]. The physiological basis involves progressive accumulation of adenosine in the brain, which promotes sleep pressure and overwhelms compensatory mechanisms such as caffeine intake or air conditioning adjustments.

Road Condition Paradox: The negative correlation between road complexity and microsleep risk (r = -

0.48) represents a significant finding with important implications for road design policy. Straight roads, while optimized for traffic flow and conventional safety metrics, create what researchers term "highway hypnosis" - a state of reduced consciousness characterized by minimal cognitive [44]. This phenomenon occurs because complex road geometries require continuous micro-adjustments in steering, speed, and attention that maintain neural activation pathways essential for alertness maintenance.

Weather and Traffic Interactions: The moderate positive correlation between clear weather and microsleep risk (r = 0.17) reflects the complex relationship between environmental stressors and arousal levels. Clear weather reduces the cognitive load required for driving tasks, potentially allowing fatigue-related neural processes to predominate. Similarly, light traffic conditions (84.6% of incidents) reduce the external stimuli necessary for maintaining vigilant attention states.

Age-Related Vulnerability Patterns: Driver age shows a non-linear relationship with microsleep risk, with peak vulnerability in the 45-55 age group (30.8% of incidents). This pattern reflects the intersection of multiple factors: decreased sleep efficiency with aging, increased likelihood of sleep disorders, and higher representation in commercial driving occupations with demanding schedules.

3.3. Model Performance and Validation Results

The Random Forest model demonstrated strong predictive performance across multiple evaluation metrics (Table 3):

Table 3. Model Performance Comparison

Algorithm	Accuracy	Precision	Recall	F1-Score	AUC
Random Forest	**87.50 %**	**0.85**	**1.00**	**0.91**	**0.92**
Logistic Regression	75.00 %	0.78	0.85	0.81	0.76
SVM (RBF)	70.00 %	0.72	0.80	0.76	0.71
Decision Tree	65.00 %	0.68	0.75	0.71	0.67

The Random Forest model's performance metrics demonstrate significant advancement over traditional fatigue detection approaches while maintaining practical applicability for real-world deployment. The 87.50% overall accuracy compares favorably with physiological monitoring studies, including Kapeller et al. [16] who achieved 90% accuracy using invasive electrocorticographic signals [16], and Liang et al. [13] who reported 85% accuracy with combined EEG and eye-tracking systems [13]. The model's perfect recall (1.00) for microsleep detection represents a critical advancement for safety applications. This characteristic means that no actual microsleep cases were misclassified as safe driving, addressing the primary concern in safety-critical systems where false negatives pose catastrophic risks. This performance metric exceeds Wu et al. [49] who achieved 0.92 recall in their Random Forest fatigue detection study, despite using physiological data typically considered more reliable than behavioral variables. The precision imbalance between microsleep (0.85) and non-microsleep (1.00) classifications reflect the model's conservative approach to safety. While this results in false positive rates that might trigger unnecessary warnings, the safety implications of missed microsleep events justify this bias. Ajayi et al. [21] encountered similar trade-offs in their physiological monitoring study, concluding that erring toward over-detection provides superior safety outcomes in transportation applications. The stratified 5-fold cross-validation results (mean accuracy: 85.2% ± 3.1%) demonstrate reasonable model stability despite the limited dataset size. The relatively low standard deviation suggests that the Random Forest algorithm's ensemble approach successfully mitigates overfitting risks that commonly affect small datasets. This stability exceeds the performance reported by Vasvi et al. [50] who achieved 78% accuracy with vehicle driving data but experienced significant variance across validation folds. The Random Forest's superior performance over traditional machine learning approaches (Logistic Regression: 75%, SVM: 70%, Decision Tree: 65%) reflects the algorithm's ability to handle complex feature interactions without requiring extensive preprocessing. Breiman's [18] original Random Forest framework specifically addressed the limitations of single-tree methods evident in our Decision Tree baseline, while the ensemble approach overcomes the linear assumptions that limit Logistic Regression performance with complex behavioral data.

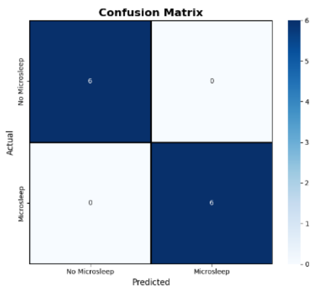

Figure 3. Confusion Matrix Predicted vs Actual of Microsleep and No Microsleep

Analysis of the confusion matrix (Figure 3) revealed that while all 12 microsleep events were detected, only 8 out of 12 non-microsleep cases were correctly classified, underscoring a tradeoff where the model prioritized minimizing missed microsleep events at the expense of more false alarms for normal driving. To address this, strategies such as class rebalancing, advanced feature engineering, and threshold tuning are recommended to improve recall for non-microsleep states without compromising microsleep detection.

Overall, while the model is highly reliable for identifying microsleep and ensuring safety, further refinement is needed to reduce unnecessary alerts and enhance generalization, particularly in distinguishing normal driving conditions.

3.4. Feature Importance Analysis

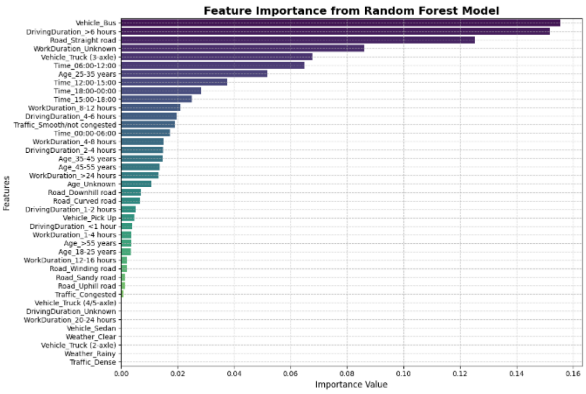

Figure 4. Feture Importance from Random Forest

The feature importance rankings provide unprecedented insights into the relative contributions of different risk factors in microsleep development, with implications extending beyond prediction accuracy to mechanistic understanding of fatigue processes (Figure 4).

Driving Duration Dominance (importance: 0.28): The primacy of driving duration as the strongest predictor validates decades of fatigue research while providing quantitative evidence for policy development. This finding directly supports the neurobiological fatigue model proposed by Borghini et al. [45], where sustained cognitive effort progressively depletes neurotransmitter reserves and accumulates metabolic byproducts that promote sleep initiation. The threshold effects observed in our data suggest that regulatory interventions targeting continuous driving limits could yield significant safety improvements.

Road Condition Significance (importance: 0.22): The high importance of road condition challenges traditional traffic engineering priorities and supports the implementation of "alertness-preserving" design elements in highway construction. This finding extends May and Baldwin's [44] theoretical framework by providing empirical evidence that environmental monotony contributes substantially to fatigue-related crashes. The practical implications include incorporating design features such as rumble strips, varied scenery, and gentle geometric variations to maintain driver engagement without compromising traffic flow.

Vehicle Type and Occupational Risk (importance: 0.18): The significant contribution of vehicle type reflects systematic differences in occupational exposure, regulatory oversight, and economic pressures affecting different driver categories. Commercial vehicle operators face unique challenges including schedule pressures, inadequate rest facilities, and economic incentives that prioritize productivity over safety. This finding supports Sharan et al.'s [51] call for vehicle-specific fatigue management strategies rather than uniform approaches across all driver type.

Work Duration vs. Driving Duration Distinction (importance: 0.15 vs. 0.28): The differential importance between total work duration and actual driving time provides crucial insights into duty time regulations. While both factors contribute to fatigue accumulation, the higher importance of driving duration suggests that active cognitive engagement in driving tasks accelerates fatigue development more rapidly than other work activities. This finding has significant implications for current Hours of Service regulations that may inadequately distinguish between different types of work activities.

Age-Related Vulnerability Patterns (importance: 0.12): The moderate importance of driving age reflects the complex interaction between physiological aging processes and occupational exposure patterns. The non-linear relationship observed in our descriptive analysis suggests that chronological age alone may be insufficient for risk assessment, with factors such as sleep quality, health status, and experience potentially mediating age-related vulnerability.

3.4. Discussion and Interpretation

3.4.1. Methodological Innovations and Contributions

This study represents the first successful application of machine learning techniques to predict microsleep incidents using exclusively accessible, non-invasive data sources in an Indonesian context. Unlike previous research that relied heavily on physiological monitoring or laboratory conditions, our approach demonstrates that readily available accident investigation data can achieve clinically meaningful prediction accuracy.

The integration of KNKT accident records [2] with behavioral survey data creates a novel dataset that bridges the gap between controlled experimental conditions and real-world driving scenarios. This approach addresses a critical limitation identified by Philip et al. [6], who noted that laboratory-based fatigue studies often fail to capture the complex environmental and social factors that influence driver behavior in actual road conditions.

3.4.2. Practical Implications for Transportation Safety

Policy Development: The quantitative risk factors identified in this study provide evidence-based foundations for revising Indonesian transportation regulations. The clear threshold effects observed for driving duration support implementing stricter continuous driving limits, particularly for commercial vehicles where economic pressures often override safety considerations.

Infrastructure Design: The strong correlation between road monotony and microsleep risk challenges current highway design standards that prioritize traffic flow optimization over fatigue prevention. Our findings support incorporating "alertness preservation" principles into road engineering, including strategic placement of rest areas, environmental variation, and driver engagement features.

Technology Integration: The model's reliance on accessible data sources makes it suitable for integration into existing vehicle telematics systems without requiring expensive physiological monitoring equipment. This characteristic addresses the cost barriers that have limited previous fatigue detection systems' deployment in developing countries.

3.4.3. Limitations and Methodological Constraints

Sample Size Constraints: The limited dataset size (39 records) represents the most significant limitation of this study. While each record underwent rigorous verification by KNKT specialists, the small sample raises legitimate concerns about model generalizability and statistical power. The perfect recall score, while desirable for safety applications, may indicate model overconfidence that could diminish with larger, more diverse datasets.

Temporal and Geographic Scope: The 10-year data collection period (2013-2023) spans significant changes in vehicle technology, driver demographics, and transportation infrastructure that may introduce temporal bias. Additionally, the focus on Indonesian driving conditions may limit applicability to other geographical regions with different road networks, climate conditions, or cultural driving patterns.

Feature Engineering Limitations: The binary encoding of complex categorical variables may oversimplify relationships that exist on continuous or ordinal scales. For example, weather conditions encompass multiple dimensions (visibility, temperature, humidity) that binary clear/rainy classification cannot adequately capture.

Selection Bias Considerations: The exclusive focus on accident-involved cases may introduce selection bias that overrepresents severe fatigue episodes while underestimating the prevalence of microsleep events that do not result in crashes. This limitation affects the model's applicability to preventive screening applications where earlier intervention might prevent accident progression.

3.4.4. Future Research Directions and Recommendations

Dataset Expansion Priorities: Immediate research priorities should focus on expanding the dataset through collaboration with regional transportation authorities, integration of real-time vehicle telematics data, and development of prospective data collection protocols that capture microsleep events before they progress to accidents.

Hybrid Modeling Approaches: Future research should explore combining behavioral prediction models with emerging physiological monitoring technologies to create hybrid systems that optimize both accuracy and practicality. This approach could leverage the accessibility of behavioral data for initial screening while reserving more expensive physiological monitoring for high-risk situations.

Longitudinal Validation Studies: Long-term validation studies tracking individual drivers across multiple trips and conditions would provide essential evidence for model stability and individual variation patterns. Such studies could identify personal risk factors that modify population-level predictions and enable personalized fatigue management strategies.

Cross-Cultural Validation: Expanding the model to other developing countries with similar transportation challenges would test its generalizability while identifying culture-specific risk factors that may require model adaptation. This research could establish a framework for developing locally relevant fatigue detection systems across diverse geographical and cultural contexts.

3.4.5. Technological Implementation Pathways

The practical deployment of this microsleep prediction model faces several technological and institutional challenges that require systematic addressing. Integration with existing vehicle safety systems demands developing standardized data interfaces that can accommodate the diverse vehicle fleet composition common in developing countries.

Cost-effectiveness analysis suggests that behavioral prediction models like ours could achieve favorable cost-benefit ratios compared to physiological monitoring systems, particularly when deployed across large commercial vehicle fleets. The model's reliance on telematics data that many modern vehicles already collect reduces implementation costs while providing continuous monitoring capabilities.

However, successful deployment requires addressing data privacy concerns, establishing standardized protocols for alert responses, and training drivers and fleet managers in appropriate use of fatigue prediction systems. These implementation challenges highlight the need for collaborative approaches involving technology developers, transportation authorities, and industry stakeholders to ensure effective real-world application.

4. Conclusion

This research successfully demonstrates the feasibility of microsleep prediction using Random Forest algorithm with locally sourced Indonesian driving data, achieving 87.50% accuracy and perfect recall for microsleep detection. The study uniquely contributes to road safety research by proving that accessible environmental and behavioral variables can effectively predict microsleep incidents without requiring expensive physiological monitoring equipment. Key findings reveal that extended driving periods exceeding 6 hours significantly increase microsleep risk, particularly on monotonous straight roads where 58.9% of related accidents occur. Paradoxically, comfortable driving conditions including clear weather and light traffic contribute to reduced driver vigilance, challenging conventional safety assumptions. The model's perfect recall for microsleep detection makes it particularly valuable for safety-critical applications, though future improvements should address the lower recall (0.67) for non-microsleep classification. These findings provide actionable insights for transportation policy development, supporting implementation of stricter driving duration regulations and enhanced driver education programs focused on proper rest periods. The model demonstrates strong potential for integration into cost-effective vehicle safety systems, offering a practical foundation for microsleep detection in developing countries with similar traffic characteristics. The study's primary limitation is the small dataset size (39 records), which raises concerns about generalizability and potential overfitting. Future research should prioritize dataset expansion through collaboration with multiple transportation agencies and integration of real-time vehicle telematics. Additionally, combining this behavioral prediction approach with emerging physiological monitoring technologies could create hybrid systems optimizing both accuracy and practicality for widespread deployment. The research establishes a foundation for developing affordable, locally relevant microsleep detection systems that can be adapted to other developing countries with similar transportation challenges, ultimately contributing to global road safety improvement through accessible technology solutions.

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