



## Top 15 New Technology Trends 2023

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#### **Al and Automation**

- Al in Healthcare
- Automation in Manufacturing
- Al in Customer Service
- Al and Cybersecurity



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WHIZLABS

#### Blockchain

- Blockchain in Supply Chain Management
- O Decentralized Finance (DeFi)
- NFTs and Digital Ownership

#### **5G Networks**

- Enhanced Mobile Broadband (eMBB)
- Massive Machine Type Communications (mMTC)
- O Ultra-Reliable Low-Latency Communications (URLLC)

#### **Quantum Computing**

- Quantum Cryptography
- Quantum Machine Learning
- Quantum Simulation

#### **Edge Computing**

- Edge AI
- Edge Analytics
- Edge Security

### Augmented Reality (AR)

- AR in Retail
- AR in Education
- AR in Gaming



#### VR in Healthcare

Virtual Reality (VR)

- VR in Education
- VR in Gaming



- Virtual Economies
- Social Metaverse

#### **Space Technology**

- Space Tourism
- Space Mining
- Space Debris Cleanup





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#### **Biometrics**

- Facial Recognition
- Voice Recognition
- Fingerprint Recognition



#### Cybersecurity

- Zero Trust Security
- Al in Cybersecurity
- Cybersecurity Regulations

#### **Cloud Computing**

- Hybrid Cloud
- O Edge Cloud
- Serverless Computing



### Internet of Things (IoT)

- Smart Homes
- Smart Cities
- Industrial IoT



- XR in Architecture and Design
- XR in Sports

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XR in Entertainment

#### Robotics

- Collaborative Robots (Cobots)
- Autonomous Robots
- Medical Robotics





# Emerging Technologies











Source: ChatGPT:)





## Data Quality:

the model's performance.



## Model Accuracy:

• High-quality training data is essential for building accurate Al models. Data should be clean, labeled correctly, and representative of the problem domain. Data preprocessing and cleansing are critical to ensure

• The primary measure of AI quality is its accuracy in making predictions or classifications. This requires careful model selection, training, and evaluation to achieve desired performance levels.



### Model Robustness:

 Al systems should be tested for their ability to handle a wide range of input data, including edge cases and outliers. Robustness testing "helps"
ensure the system's reliability in realworld scenarios.



## Explainability and Interpretability:

 For many AI applications, especially those with high stakes (e.g., healthcare, finance, and autonomous systems), it's essential to make the model's decisions explainable and interpretable. This can help gain user trust and satisfy regulatory requirements.





### **Performance and Scalability:**

 Al models should be able to perform efficiently and scale as needed to handle real-world workloads. Performance optimization is often necessary to ensure that Al systems can meet user expectations.



**Continuous Monitoring and Maintenance:** 

• Al models can degrade over time as the data distribution shifts or the environment changes. Regular monitoring and maintenance are essential to ensure that the Al system remains accurate and reliable.



Software quality for artificial intelligence applications is multifaceted and requires careful consideration of data, model, ethics, security, and more. Thorough testing, monitoring, and maintenance are crucial to ensure that Al systems remain effective and reliable in a rapidly evolving field.



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## **Automated Testing:**

 Al-powered testing tools can automate test case generation, execution, and analysis. These tools can identify defects, vulnerabilities, and performance issues more efficiently and comprehensively than manual testing.



## **Code Analysis and Review:**

 Al can assist in code review by identifying coding standards violations, potential bugs, and code smells. Tools like static code analyzers and linters can use Al to enhance code quality.



2019 IEEE/ACM 27th International Conference on Program Comprehension (ICPC)

# Learning a Classifier for Prediction of Maintainability based on Static Analysis Tools



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TABLE I ANALYZED SOURCE CODE

	JUnit 4 (4.11	) System C
	Software Dev.	Insurance
nage-	Testing Fram	e- Damage Evalu-
em	work	ation System
	2014	2014
rd 👘	Open-source	In-house
2	44.6k LOC	380k LOC
	10k LOC	41k LOC
es	75 Classes	110 Classes

#### TABLE II EXPERIMENT RESULTS

racy	Precision	Recall	<b>F-Score</b>
87	0.7967	0.8087	0.8009
71	0.7693	0.7971	0.7757
71	0.7577	0.7971	0.7566
02	0.6430	0.7101	0.6540
67	0.6667	0.6667	0.6667



## **Bug Detection and Prediction:**

• Al can analyze historical data to predict potential **software bugs**, enabling proactive bug fixing. It can also identify anomalies in code or system behavior that might indicate underlying issues.



to detect anomalies in real-time, helping identify



2019 26th Asia-Pacific Software Engineering Conference (APSEC)

# **Run-time Safety Monitoring Framework for AI-based Systems: Automated Driving Cases**

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### **Requirements Analysis:**

- Al can help ensure that software
  - requirements are clear, complete, and free from contradictions by analyzing and validating the requirements documents.



### Natural Language Processing (NLP):

 Al-powered NLP tools can improve communication among team members and stakeholders, making it easier to understand and document software requirements, issues, and changes



2018 ACM/IEEE 5th International Workshop on Requirements Engineering and Testing

# Ambiguous Software Requirement Specification Detection: An Automated Approach

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	Process	Output	Table 6: Classification Performance Model (accuracy)					
1			1911gragier	AllData	*DataH	*DataB	*DataHB	
	1. Data Cellection	Rew Data	OneR	78.06	65.78	60.78	65.78	
5		1 1	Naive Bayes	80.22	65.33	58.11	67.22	
5	2. Dooument Processing	i i i	Logistic Reg.	80.94	67.83	54.72	66.67	
12		Fibered Data	k-NN	71.89	67.89	58.22	69.83	
0			Decision Table	78.06	62.00	56.72	63.28	
1 for	J. lext Processing		Decision Stump	77.17	48.89	57.78	52.33	
-	4. Text Clarenteaton and Evenuation		J48	82.67	71.17	57.83	70.89	
			Random Forest	89.67	70.44	59.06	76.56	
1884	Universite Analysis	Classification	Random Tree	80.89	68.22	59.00	71.39	
0	Classification Algorithm Selection Evaluation of Feature-words set		* Data_H used feature-words suggested by Haron et. al [17];					
			*Data_B used feature-words mentioned in Berry et. al. [7] ; and					
	Parketinance		*DataHB is	s the combir	ation of Da	ataH and I	DataB	
See.	S. Putting on Development and	1 Determent	n <mark>g sistem</mark> akan mal	klumat dan u	ntuk telah	mohon guna	boleh proses	
Noo In	Manufactor and	Validation	ho) (system) (will) (info	rmation) (and)	(for) (already)	(apply) (use)	(can) (process)	
- and			0 0	1 0	0 0	0 0	1 0	
12		- 1	1 0	0 0	1 0	0 0	0 0	
			0 1	0 2	3 0	0 1	0 2	
	Figure 1: Overall Approach			0 1	0 0	0 1	2 1	
				0 0	1 0	0 0	0 1	





Code Refactoring: Al can assist in refactoring code to improve maintainability, readability, and adherence to best practices, ultimately enhancing software quality.

> (IJACSA) International Journal of Advanced Computer Science and Applications, Vol. 14, No. 5, 2023

# From Monolith to Microservice: Measuring Architecture Maintainability

Muhammad Hafiz Hasan<sup>1</sup>, Mohd. Hafeez Osman<sup>2</sup>, Novia Indriaty Admodisastro<sup>3</sup>, Muhamad Sufri Muhammad<sup>4</sup> Dept. of Soft. Engineering and Information System-FSKTM, UPM, Serdang, Selangor, Malaysia<sup>1, 2, 3, 4</sup>



Preprints are preliminary reports that have not undergone peer review. They should not be considered conclusive, used to inform clinical practice, or referenced by the media as validated information.

### A Quality Driven Framework for Decomposing Legacy Monolith Applications to Microservice Architecture

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# Artificial Intelligence for Software Quality Journals The Institution of Engineering and Technology eISSN 2516-8398 Received on 24th May 2019 Revised 10th January 2020 Accepted on 3rd February 2020 E-First on 9th March 2020 doi: 10.1049/iet-cim.2019.0029 www.ietdl.org



### **Predictive Maintenance:**

 In the context of software-as-a-service (Saas) applications, AI can predict when soft components or infrastructure might fail require maintenance, reducing downtime.

IET Collaborative Intelligent Manufacturing

Research Article

# Classification model for predictive maintenance of small steam sterilisers

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Al can enhance software quality by reducing human error, automating repetitive tasks, providing insights from vast data sets, and improving the overall development and testing process. However, it is essential to use AI tools judiciously and in conjunction with human expertise to ensure the best results.



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