Past and Future of Artificial Intelligence and Concrete Design and Construction

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Iowa State University (ISU)

November 9, 2023

Contributors/Credits

- Hard working members of our research team and collaborators including, but not limited to:
  - M. Birkan Bayrak, Ph.D., Nazik Citir, Kasthurirangan Gopalakrishnan, Ph.D., Alper Guclu, Orhan Kaya, Ph.D., Sunghwan Kim, Ph.D., PE., Md Lutfor Rahman, Adel Rezaei Tarahomi, Ph.D., Md Abdullah All Sourav, Ph.D., and Sinan Kefeli
  - Other research team members/collaborators during my research career at Iowa State University (ISU) and the University of Illinois Urbana Champaign (UIUC)
  - Dedicated contributors/researchers on AI and concrete technologies related to this presentation

Acknowledgements

- Would also like to express my sincere gratitude to including, but not limited to:
  - Federal Aviation Administration (FAA)
  - Partnership to Enhance General Aviation Safety, Accessibility and Sustainability (PEGASAS): Federal Aviation Administration (FAA) Center of Excellence for General Aviation (COE)
  - Iowa Highway Research Board (IHRB)
  - Iowa Department of Transportation (DOT)
  - Iowa County Engineers Association Service Bureau (ICEASB)
  - Other funding agencies at the federal and local levels during my research career at ISU and the UIUC

Personal Context: Education

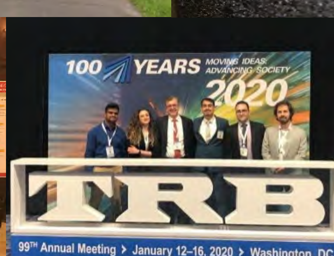
- Ph.D., University of Illinois at Urbana-Champaign, Civil Engineering, Dec. 2002
  - Dissertation: Analysis and Design of Concrete Pavement Systems Using Artificial Neural Networks
- M.S., University of Illinois at Urbana-Champaign, Civil Engineering, May 1995
- M.S., Dokuz Eylul University, Izmir, Turkey, Civil Engineering, June 1993
- B.S., Dokuz Eylul University, Izmir, Turkey, Civil Engineering, June 1989

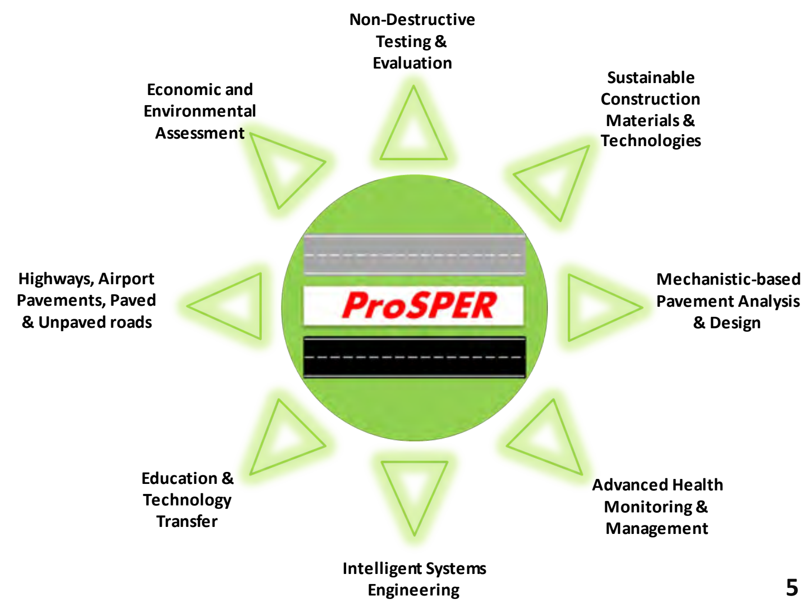
Personal Context: Research Focus Areas

- Smart, Sustainable, Durable, and Resilient Geosystems and Transportation Infrastructure systems
- Analysis and Design of Transportation Infrastructure Systems
- Sustainable Construction Materials & Technologies
- Highways, Airfield Pavements, Paved & Unpaved Roads
- Advanced Health Monitoring & Management [using Smart Sensors & Systems and Unmanned Aerials Systems (UAVs)]
- NDT & NDE of Transportation Infrastructure Systems
- Intelligent Systems Engineering & Artificial intelligence (AI) Based Applications in Engineering
- Economic and Environmental Assessment including LCCA and LCBCA
- Geotechnical Aspects of Pavement Systems
- Performance Modelling of Paved/Unpaved Roads
- Characterization of Pavement/Geo-Materials
- Sustainable Winter Maintenance (e.g., Ice- and Snow-Free Pavement Systems)
- Education & Technology Transfer





Personal Context: Achievements/Impact Highlights

- PI/Co-PI of **138 sponsored research projects**
  - **Approximately $25.2 million of project funds** including matching funds
  - Sponsored by the FHWA, the FAA, NSF, NCHRP, IA DOT, IHRB, MN DOT, MN LRRB, WI DOT, IL DOT, PCA, and other funding agencies
- **Over 410 peer-reviewed research publications** authored and co-authored (~90% has been co-authored with my graduate students and research staff) and **two US patent applications** (published and pending)
- **Over 400 invited and technical lectures** including **over 150 invited talks**
- **Over 7,300 citations and an h-index of 44** (as of November 2023 from Google Scholar)
- **More than 40 news media/TV coverages** (including NBC's Today Show and NBC's Nightly News with Lester Holt, Discovery Channel's Daily Planet Show, The Weather Channel Live, Engineering News Record (ENR) and so on) featuring Dr. Ceylan's research
- More than 30 national and international professional committees and organizations
- Have collaborated with over 100 researchers from over 30 institutions

On NBC's TODAY Show & Nightly News with Lester Holt (January 26, 2018)


Could heated airport runways melt away your winter travel headaches?

Jeff Rossen and Lindsey Bomnin
TODAY
Jan. 26, 2018 at 6:42 AM

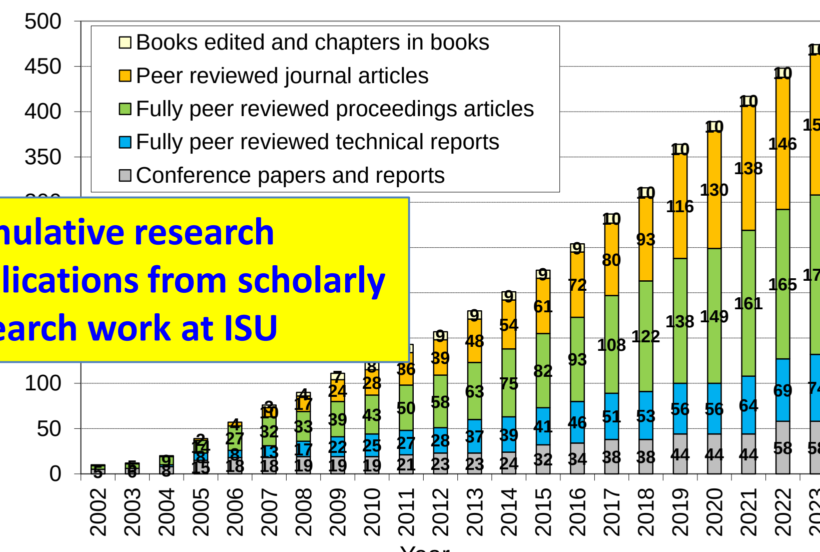
There have been thousands of flight delays and cancellations due to winter weather this year, and it's only January. Not only that: snow and ice at airports can send planes skidding off slippery runways.

Get Jeff Rossen's new book, "Rossen to the Rescue," here.

What if there were something that could fix all that? At Des Moines International Airport in Iowa, TODAY national investigative correspondent Jeff Rossen got a look at a new technology in action: heated runways and tarmacs.

HALIL CEYLAN
IOWA STATE UNIVERSITY HEAD RESEARCHER

Cumulative research publications from scholarly research work at ISU



Personal Context: Selected Concrete Pavements Related Projects

- **Federal grants/National level projects**
  - Heated Airport Concrete Pavements
  - Small Unmanned Aircraft System (sUAS) for Pavement Inspection
  - Implementing a Multiple-Slab Response Model for Top-Down Cracking Mode in Rigid Airport Pavements
  - Independent Review of the Recommended Mechanistic-Empirical Pavement Design Guide (MEPDG) and Software – New PCC Pavements
  - Models for Predicting Reflection Cracking for Hot-Mix Asphalt Overlays on PCC Pavements
  - Sensitivity Evaluation of MEPDG Performance Prediction
  - Standard Definitions for Comparable Pavement Cracking Data
  - Study Assessing the Impact to Concrete Pavement Smoothness from Curling, Warping and other Early-Age Behavior
  - Concrete Pavement Mixture Design and Analysis

- **State DOT/IHRB funded projects**
  - Implementing a Self-Heating, Electrically Conductive Concrete Heated Pavement System for the Bus Stop Enhancement Project in the City of Iowa City
  - Self-Heating Electrically Conductive Concrete Demonstration Project
  - "Prevention of Longitudinal Cracking in Iowa Widened Concrete Pavement
  - Concrete Overlay Performance on Iowa's Roadways
  - Impacts of Internally Cured Concrete Paving on Contraction Joint Spacing"
  - Impact of Curling and Warping on Concrete Pavement
  - Embedded Micro-Electromechanical Sensors and Systems (MEMS) for Monitoring Highway Structures and for Infrastructure Management
  - Performance Evaluation of Concrete Pavement Granular Subbase
  - Design and Construction Procedures for Concrete Overlay and Widening of Existing Pavements

Outline

- Introduction: Fundamentals of Concrete and Artificial Intelligence (AI)
- Advent of AI in Concrete Science and Technology
- Applications of AI in Concrete Design and Construction
- Case Studies and Success Stories: Dr. Ceylan's Research on Use of AI for Concrete Pavement Systems
- Summary

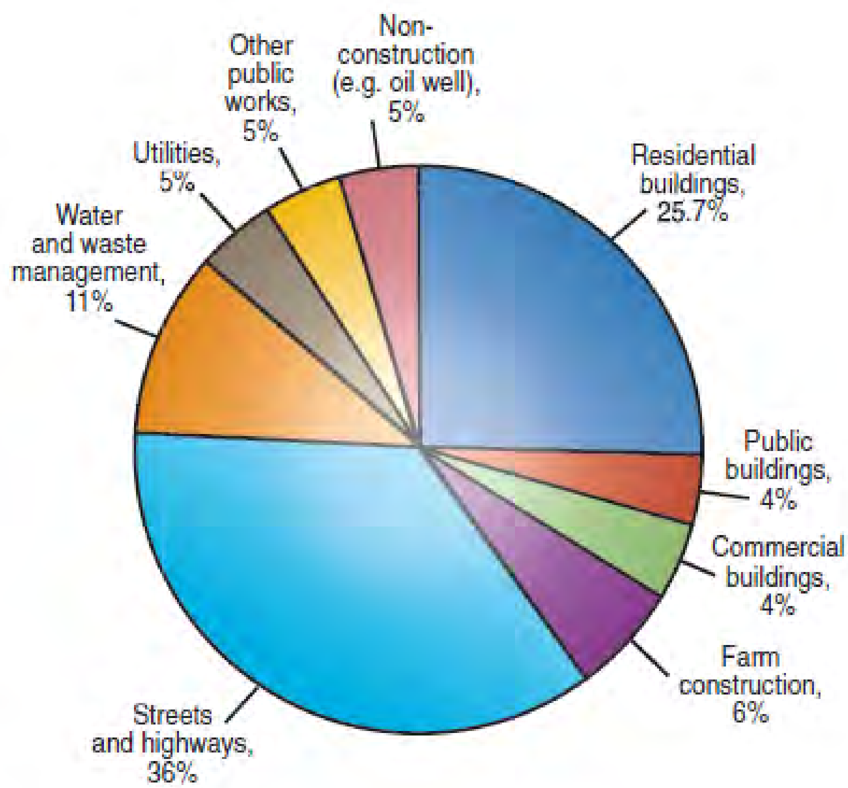
Concrete

- Concrete components
  - Cement
  - Water
  - Coarse aggregate
  - Fine aggregate
  - Supplementary cementing materials
  - Chemical admixtures

(Image source: PCA)

Applications for Concrete

Bridges
Buildings
Masonry
Parking Lots
Pavements
Residential
Transit and Rail
Soil Cement and Roller-Compacted Concrete
Waste Remediation
Water Resources



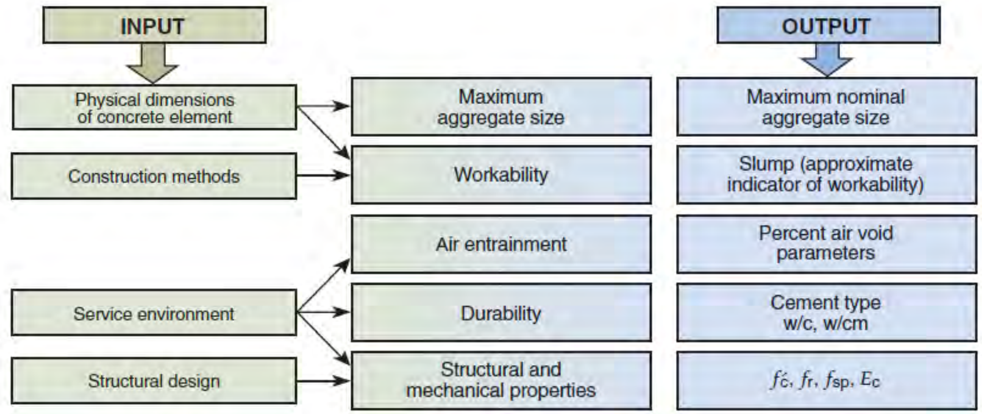
(Source: PCA 2010)

Applications for Concrete (Cont'd)

(Image source: PCA)

Concrete Design

- Material design
  - Designing and proportioning concrete mixtures



- Structural design
  - Designing dimensions of concrete structure elements and other requirements for intended use, e.g., AASHTOWare Pavement ME Design and AASHTOWare Bridge

(Image source: PCA and AASHTO)

Concrete Construction

- General steps for construction
  - Preparation before placing
  - Depositing concrete
  - Consolidation
  - Finishing
  - Jointing
  - Patching and cleaning concrete





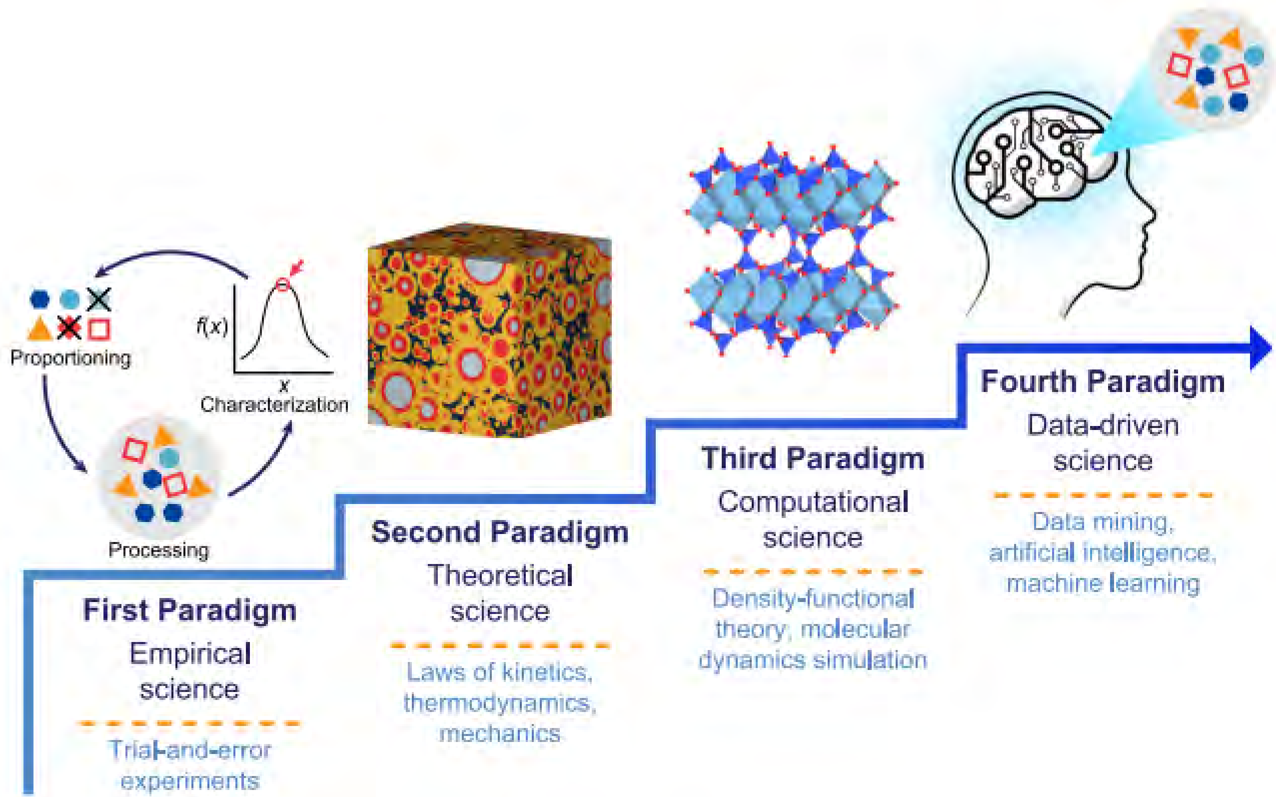

(Image source: PCA)

Challenges in Concrete Design and Construction

- A lot of variables
  - Local material properties
  - Various load types
  - Climatic conditions
  - Construction methods
  - Geometrics
  - Cost
  - Sustainability
  - Resilience
  - And many others

(Image source: PCA)

Paradigm Shift on Concrete Design and Construction



(Image source: [Li et al. 2022](#))

Artificial Intelligence (AI)

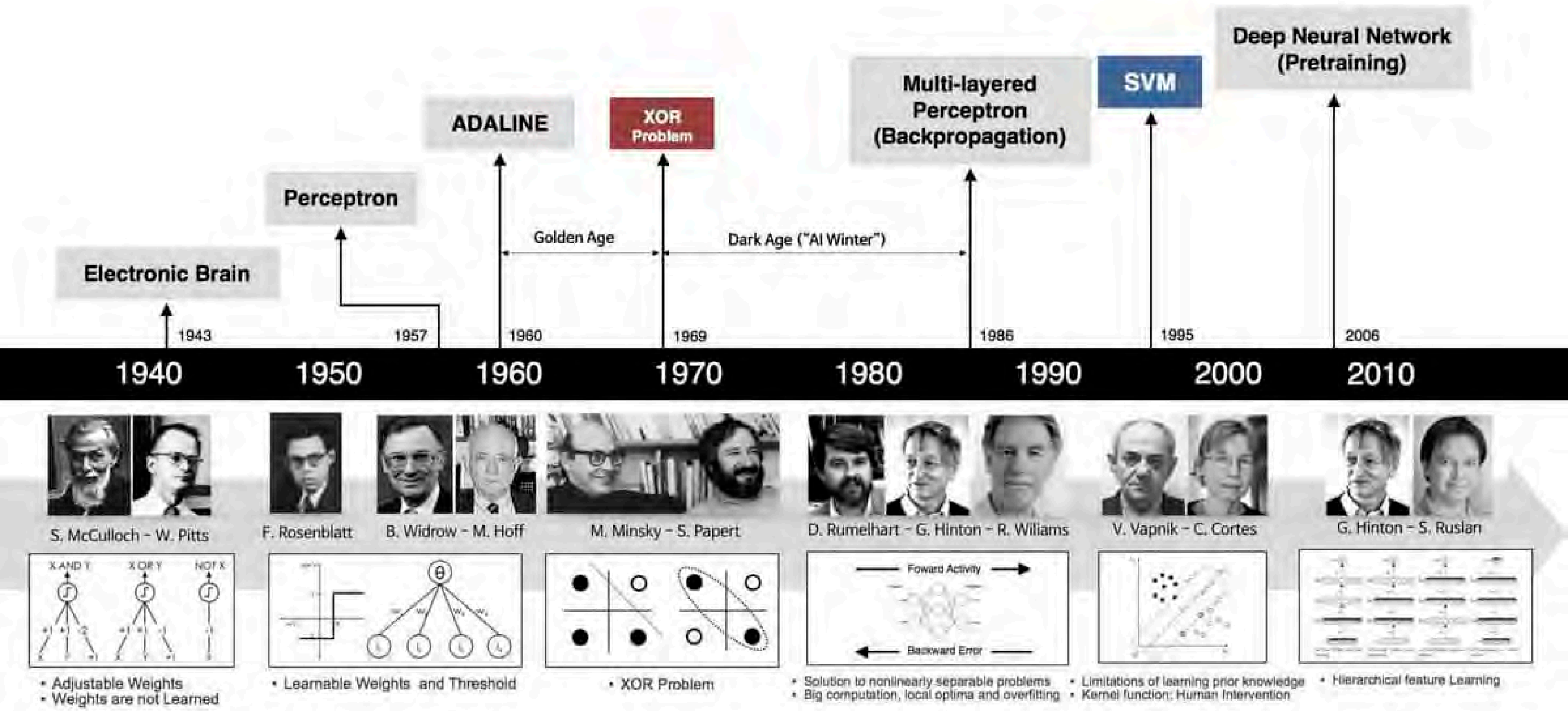
- Artificial Intelligence (AI) is the science of making things smart/intelligent
- It can be defined as:

  "Human intelligence exhibited by machines"

- AI is a broad term for getting computers to perform human tasks
  - The scope of AI is disputed and constantly changing over time

(Reference: Mayes 2017)

AI: The Past



(Reference: Samanta 2021)

AI: The Present

- AI can be general or narrow

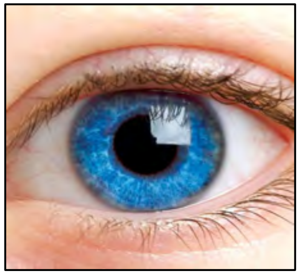
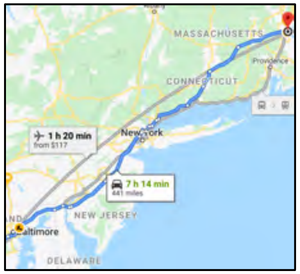
- The systems implemented today are a form of narrow AI

- A system that can do just one or a few defined things as well or better than humans, such as recognizing objects/gestures we trained* it to learn
  - *needs code written by humans to create a system capable of learning that thing

(Reference: Mayes 2017)

AI: Common Use Cases

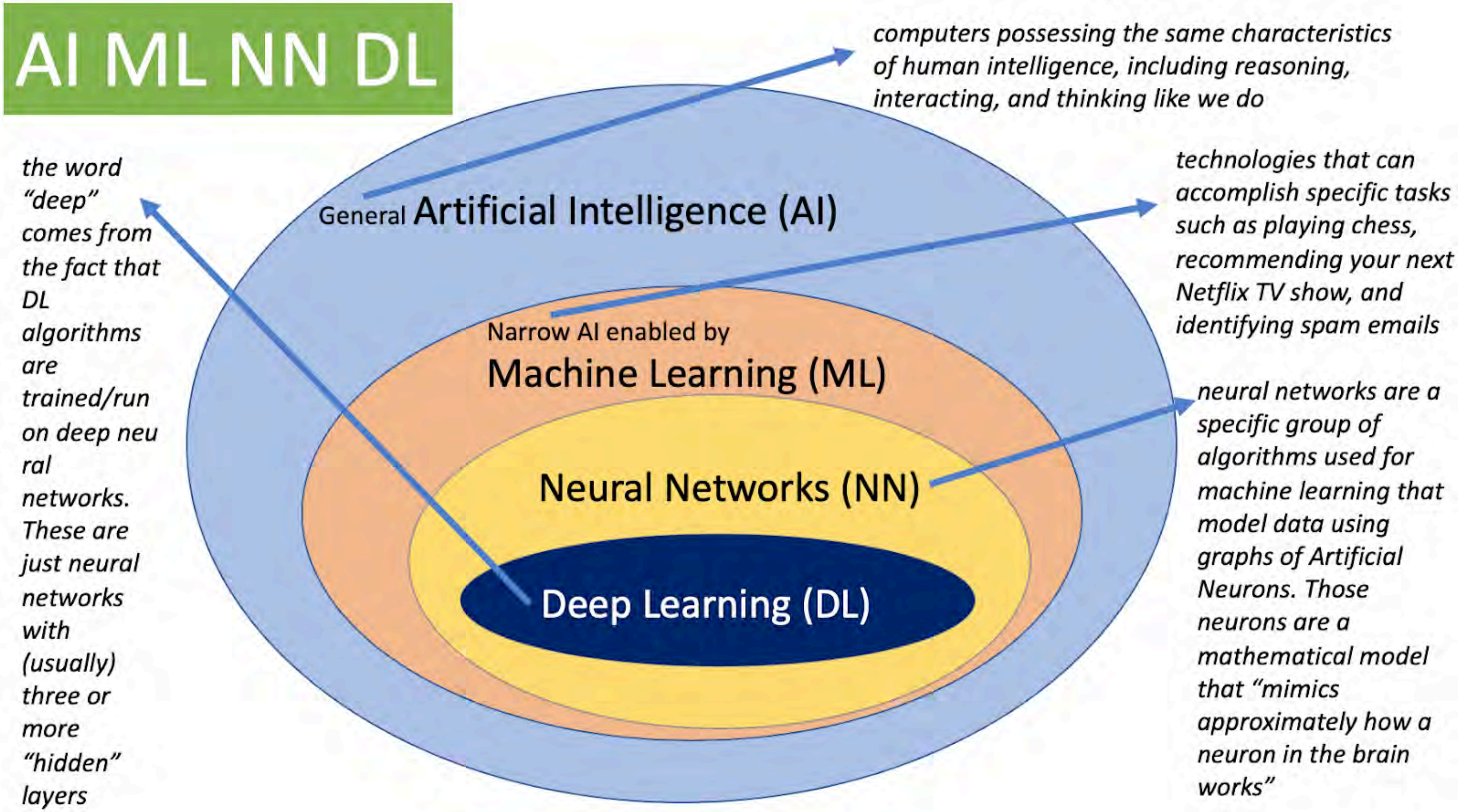
- Typical ‘narrow’ tasks include;
  - Vision
  - Natural language processing
  - Planning
  - Object recognition (e.g., vacuum cleaners)
  - Speech recognition/sound detection
  - Translation between languages
  - Prediction (given some inputs, what is the expected output for unseen examples)
  - Restoration/Transformation
  - State-of-art smart cars
  - Self-driving cars
  - Personal assistant robots, so on…



(Reference: Leshchinskiy 2021)

AI: Types



(Image Source: https://www.greatillustrations.top/ProductDetail.aspx?iid=155812016&pr=42.88)

AI: Types (Cont'd)

- AI, ML, and DL are sometimes used interchangeably but there are distinctions

- Differences among AI, ML and DL
  - The term AI, coined in the 1950s, refers to the simulation of human intelligence by machines. It covers an ever-changing set of capabilities as new technologies are developed. Technologies that come under the umbrella of AI include ML and DL.

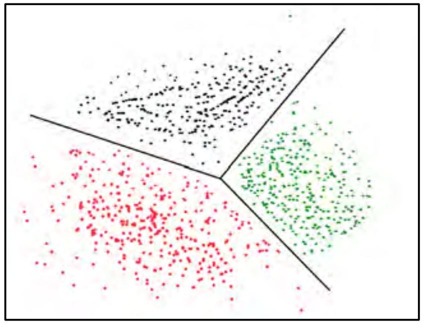
  - ML, which began in 1970s, is a form of AI based on algorithms that are trained on data. ML enables software applications to become more accurate at predicting outcomes without being explicitly programmed to do so. ML algorithms use historical data as input to predict new output values. This approach became vastly more effective with the rise of large data sets to train on.

  - DL, a subset of ML, is based on our understanding of how the brain is structured. DL uses neural networks —based on the ways neurons interact in the human brain—to ingest data and process it through multiple iterations that learn increasingly complex features of the data, including self-driving cars and ChatGPT.

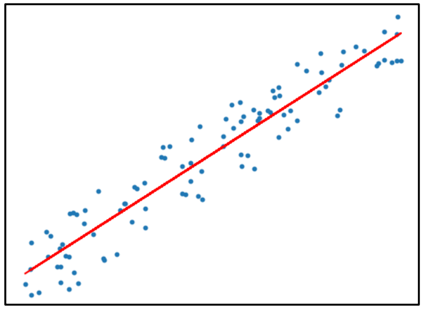
(Reference: Burns n.d., McKinsey & Company n.d.)

- ML can perform many tasks:
  1. Classification

  2. Clustering



  3. Regression



- There are 3 types of learning:
  1. Supervised

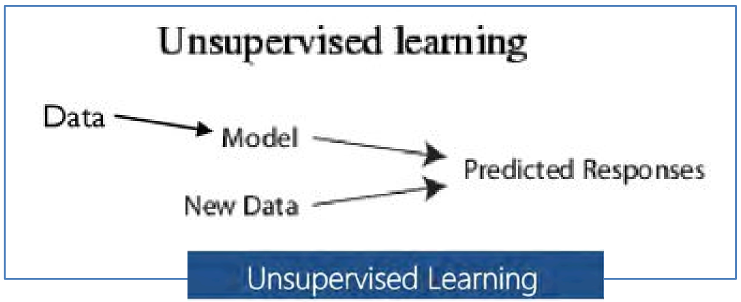
  2. Unsupervised

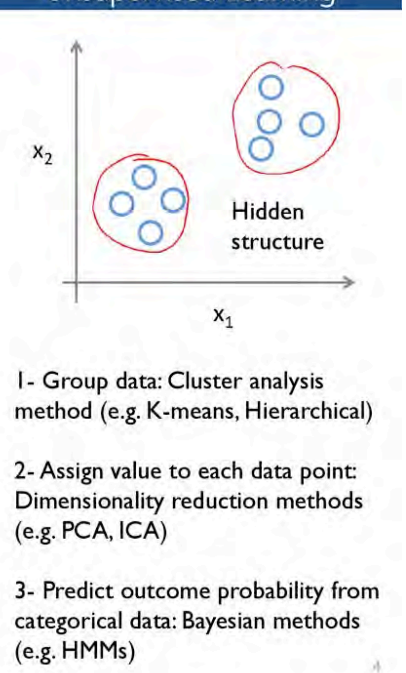
  3. Reinforcement learning

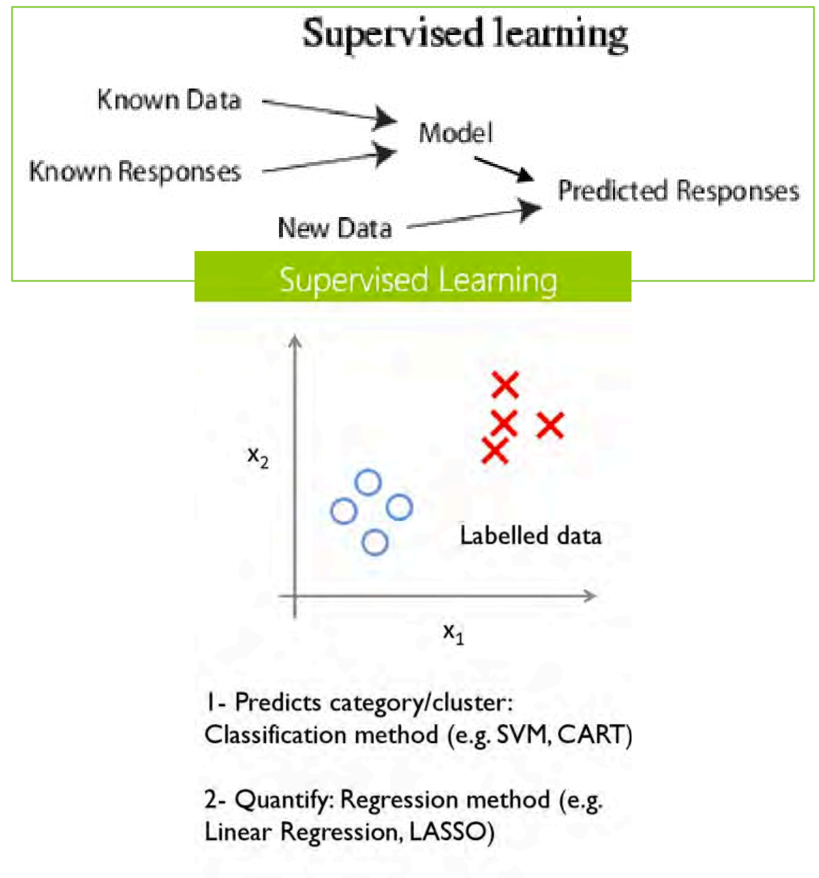
(Reference: Leshchinskiy 2021)

AI: ML (Cont'd)

- Supervised vs. unsupervised methods
  - Consideration: Categorical vs continuous data



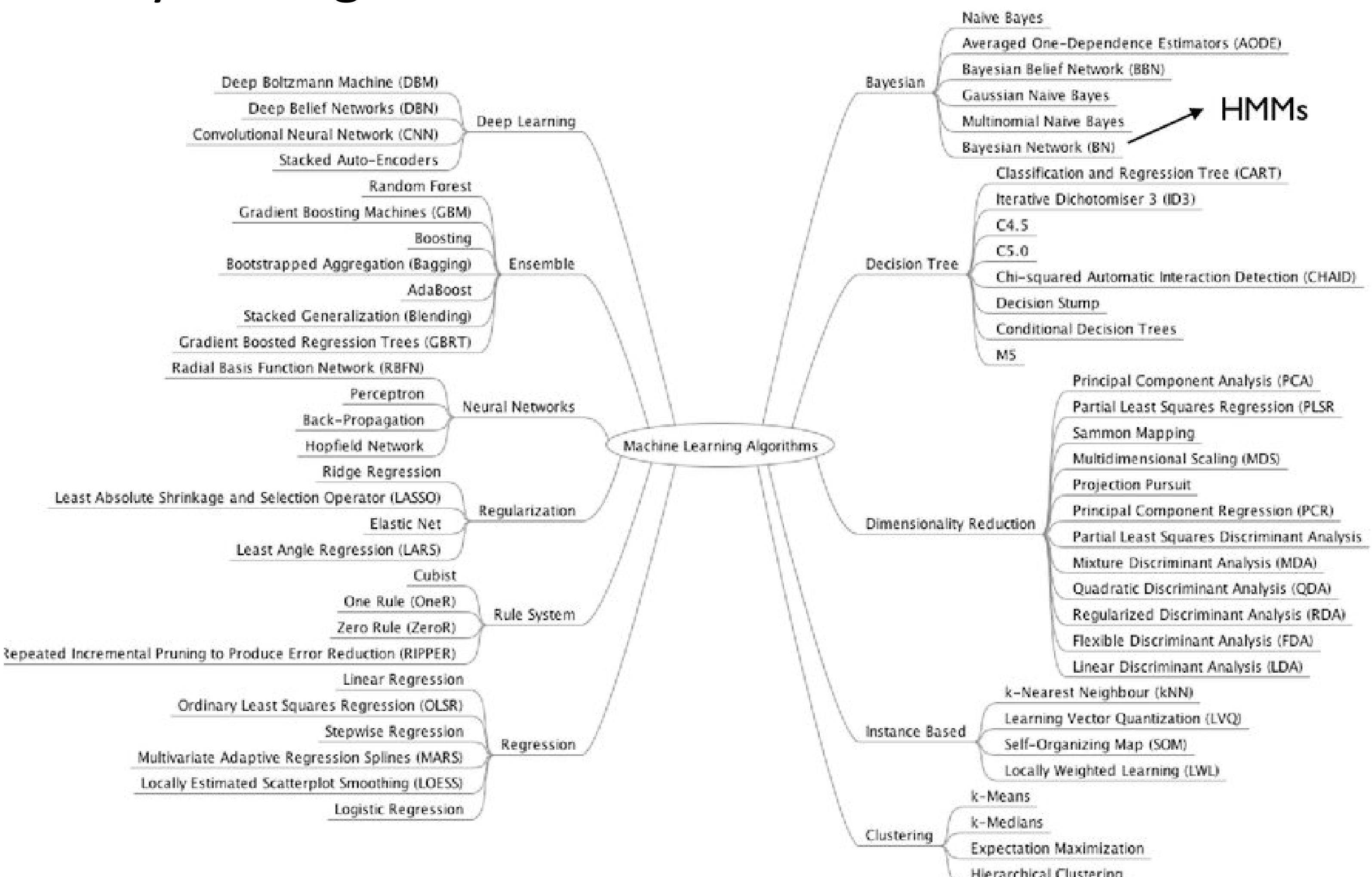




(Reference: Forsberg n.d.)

AI: ML (Cont'd)

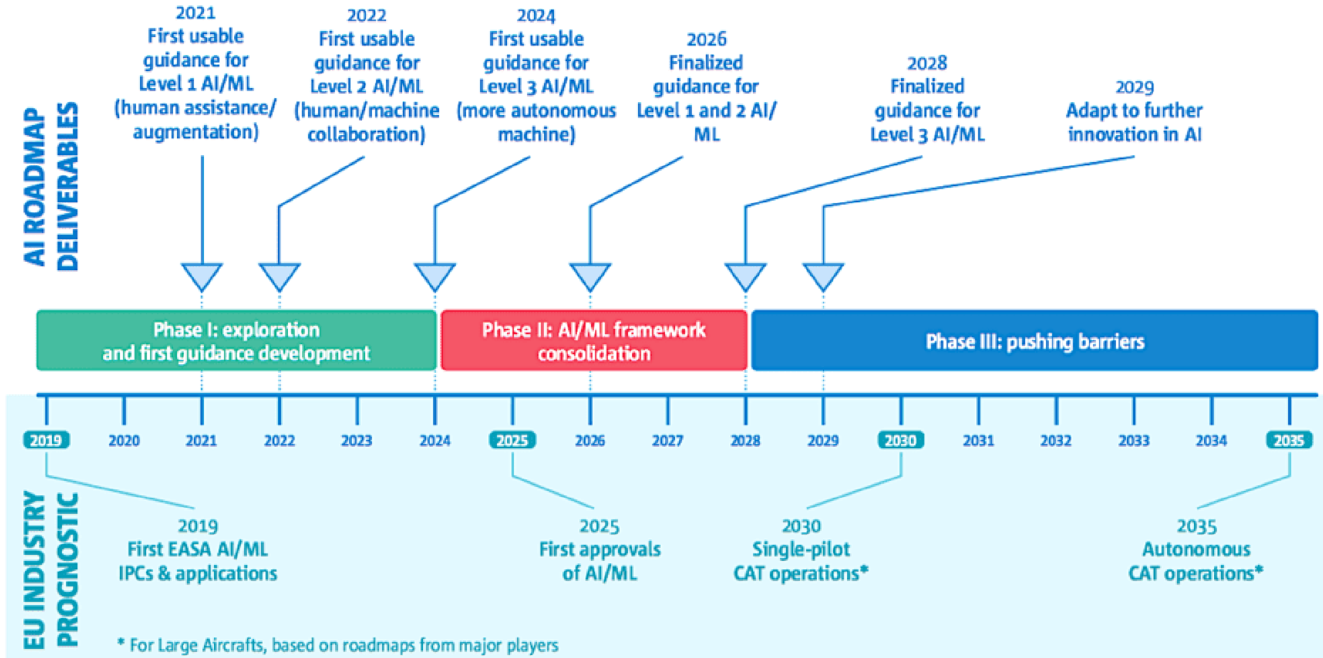
- Many ML algorithms



(Reference: Forsberg n.d.)

AI: The Future

- Self-driving vehicles and safer transportation
- Augmenting human abilities
- Increased penetration in daily life activities, and so on…



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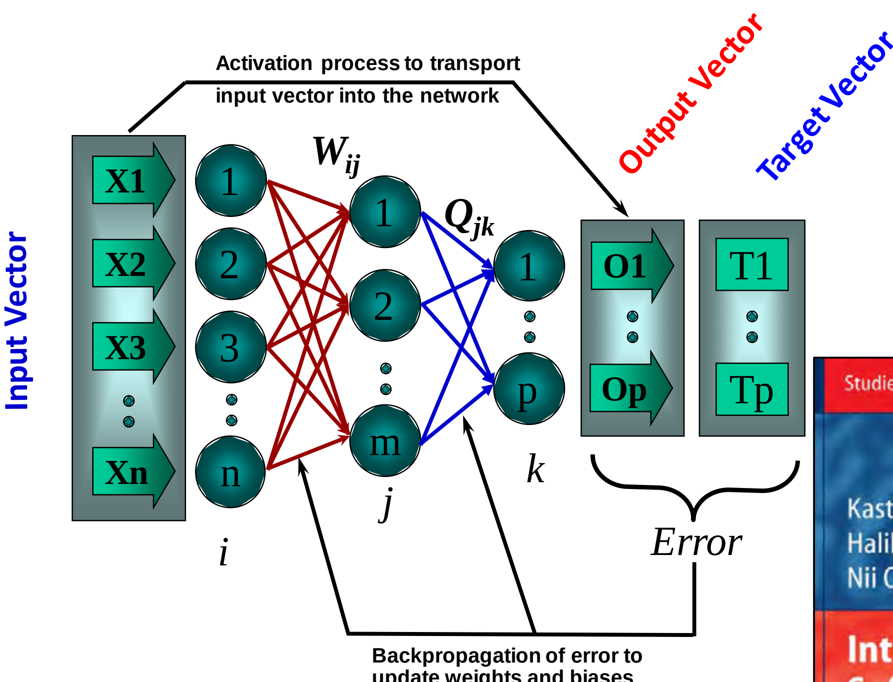
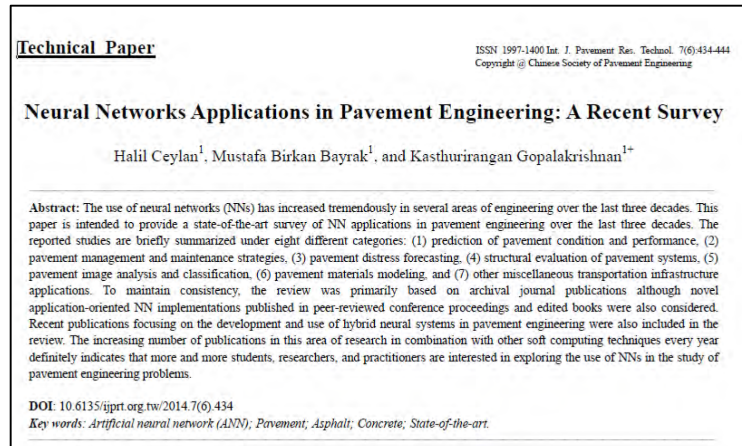
Advent of AI in Concrete Science and Technology

- Various AI technologies have been explored and used in the field of concrete science and technology




Technical Paper

ISSN 1997-1400 Int. J. Pavement Res. Technol. 7(6):434-444
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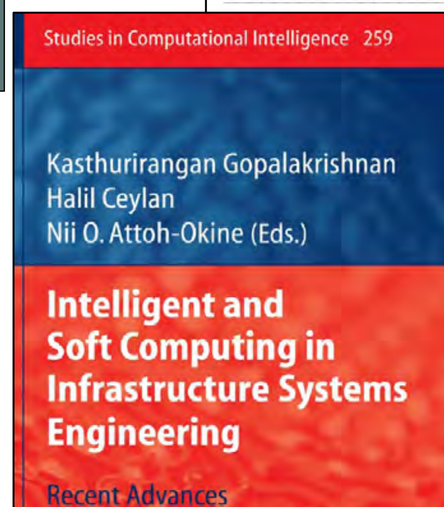
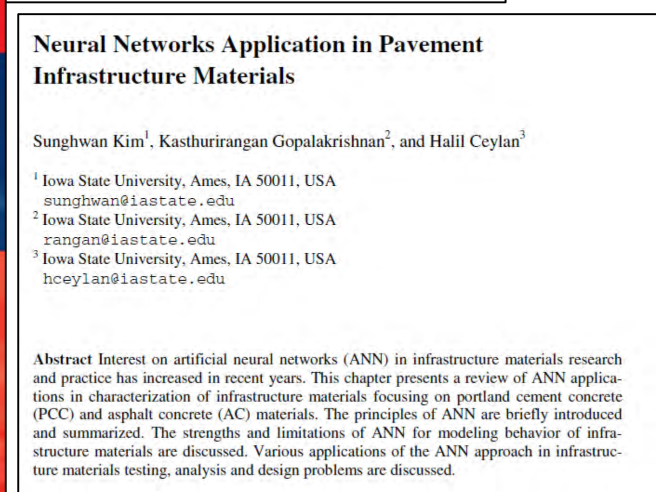
Neural Networks Applications in Pavement Engineering: A Recent Survey

Halil Ceylan[1], Mustafa Birkan Bayrak[1], and Kasthurirangan Gopalakrishnan[1+]

Abstract: The use of neural networks (NNs) has increased tremendously in several areas of engineering over the last three decades. This paper is intended to provide a state-of-the-art survey of NN applications in pavement engineering over the last three decades. The reported studies are briefly summarized under eight different categories: (1) prediction of pavement condition and performance, (2) pavement management and maintenance strategies, (3) pavement distress forecasting, (4) structural evaluation of pavement systems, (5) pavement image analysis and classification, (6) pavement materials modeling, and (7) other miscellaneous transportation infrastructure applications. To maintain consistency, the review was primarily based on archival journal publications although novel application-oriented NN implementations published in peer-reviewed conference proceedings and edited books were also considered. Recent publications focusing on the development and use of hybrid neural systems in pavement engineering were also included in the review. The increasing number of publications in this area of research in combination with other soft computing techniques every year definitely indicates that more and more students, researchers, and practitioners are interested in exploring the use of NNs in the study of pavement engineering problems.

DOI: 10.6135/ijprt.org.tw/2014.7(6).434
Key words: Artificial neural network (ANN); Pavement; Asphalt; Concrete; State-of-the-art.




Neural Networks Application in Pavement Infrastructure Materials

Sunghwan Kim[1], Kasthurirangan Gopalakrishnan[2], and Halil Ceylan[3]

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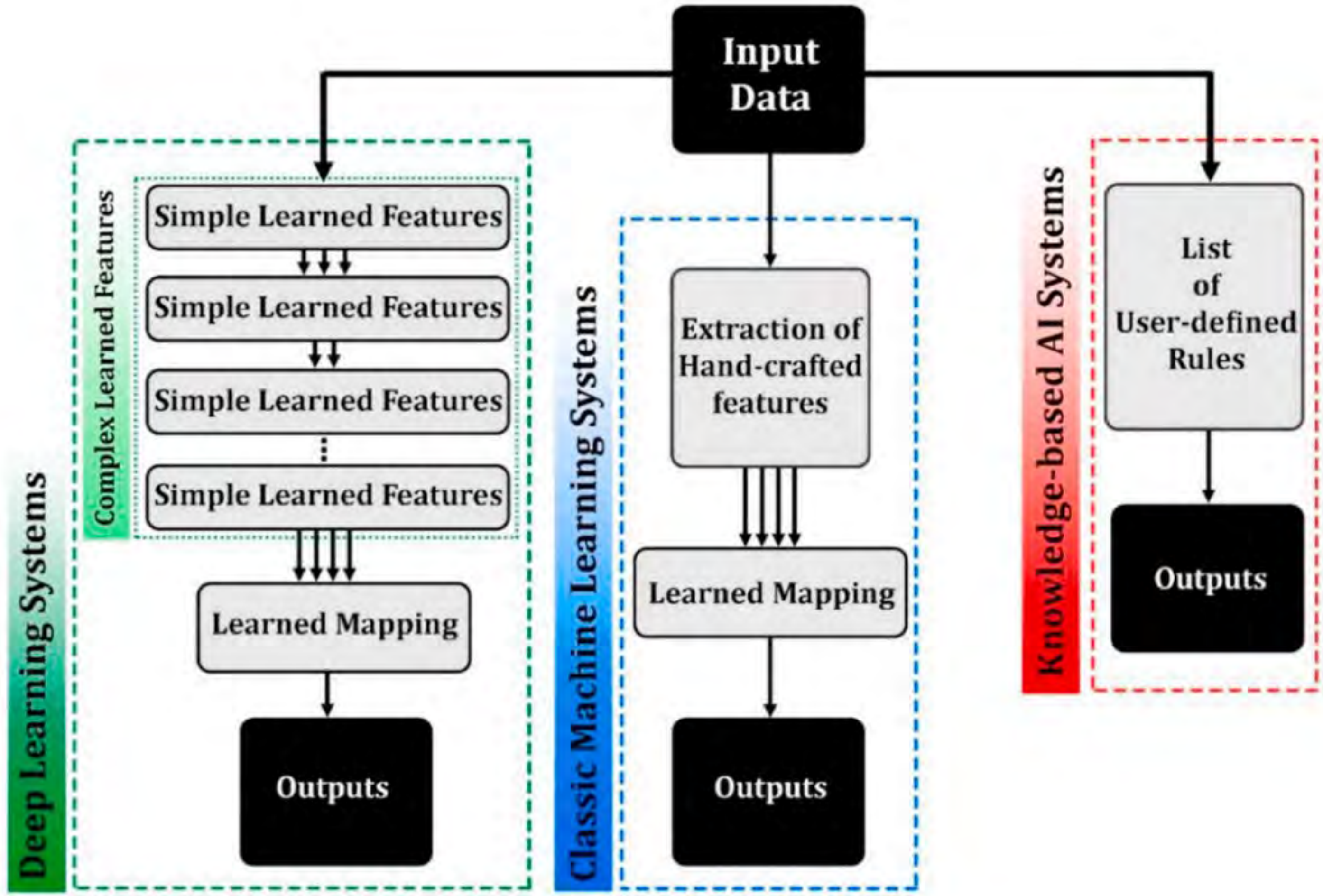
Abstract Interest on artificial neural networks (ANN) in infrastructure materials research and practice has increased in recent years. This chapter presents a review of ANN applications in characterization of infrastructure materials focusing on portland cement concrete (PCC) and asphalt concrete (AC) materials. The principles of ANN are briefly introduced and summarized. The strengths and limitations of ANN for modeling behavior of infrastructure materials are discussed. Various applications of the ANN approach in infrastructure materials testing, analysis and design problems are discussed.

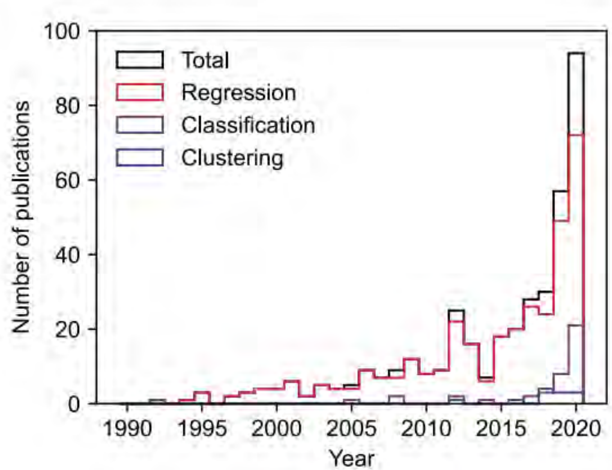
Advent of AI in Concrete Science and Technology (Cont'd)

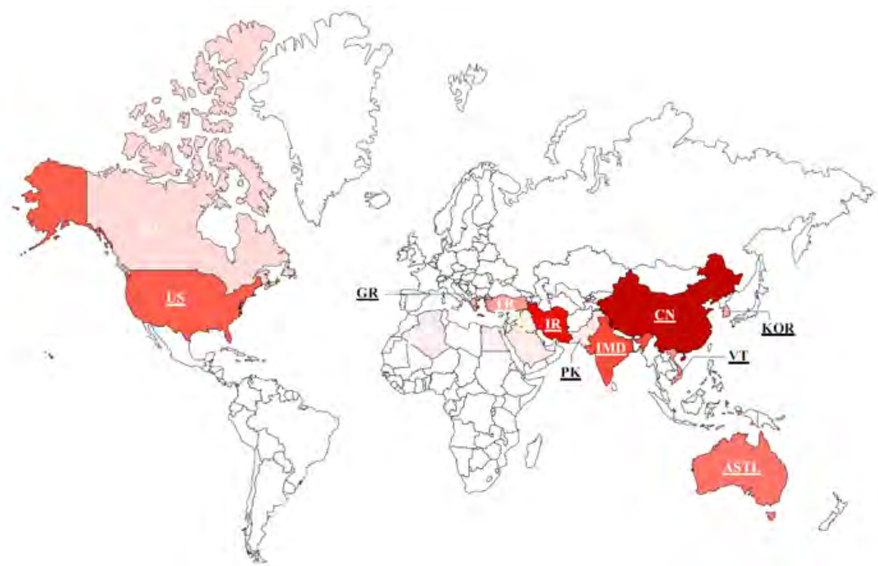


(Reference: Moein et al. 2022)

Advent of AI in Concrete Science and Technology (Cont’d)

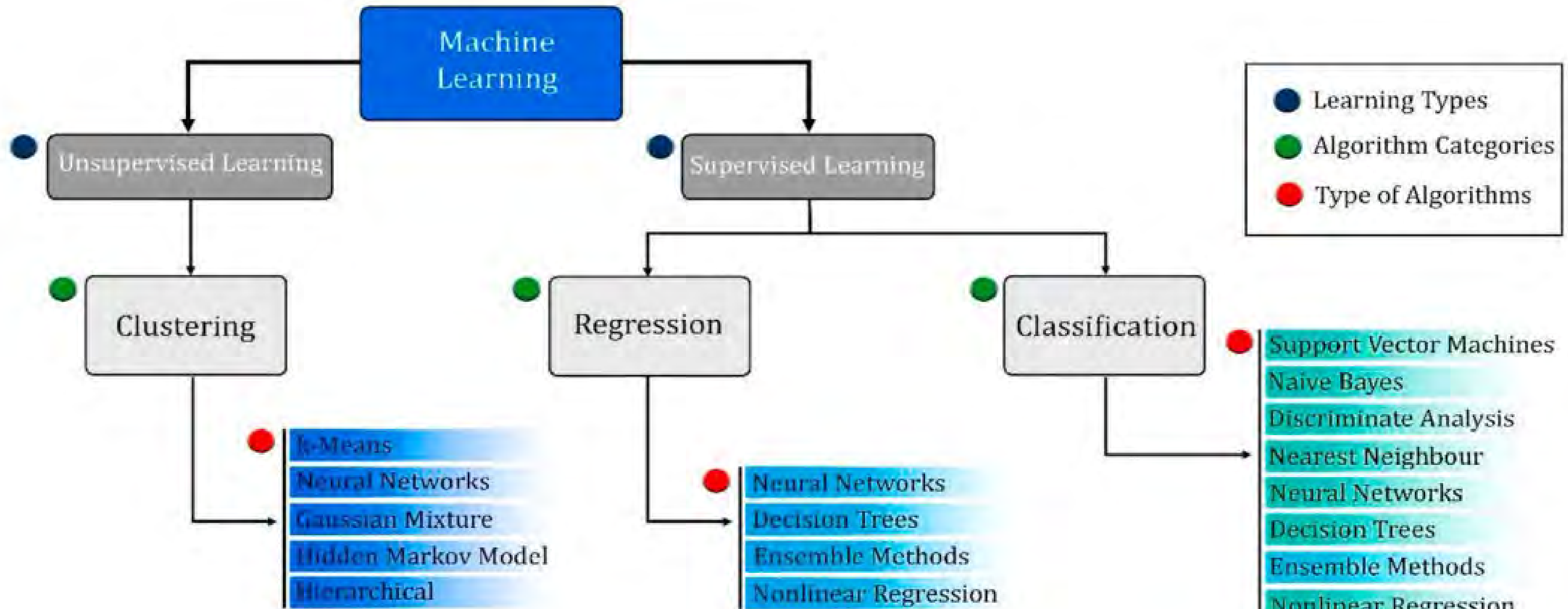
- In the late 1980s, Adeli and Paek (1986) proposed using AI technology in concrete construction
- Adeli and Yeh (1989) created a perceptron model to guide the design of concrete
  - Prototype artificial neural network (ANN) to predict concrete compressive strength
- Earliest article identified in connection to concrete and ML was published in 1992
  - Impact-Echo Signal Interpretation Using Artificial Intelligence by Pratt et al. (1992)
- Number of publications remained relatively low until 2010 but dramatically increased in 2020s





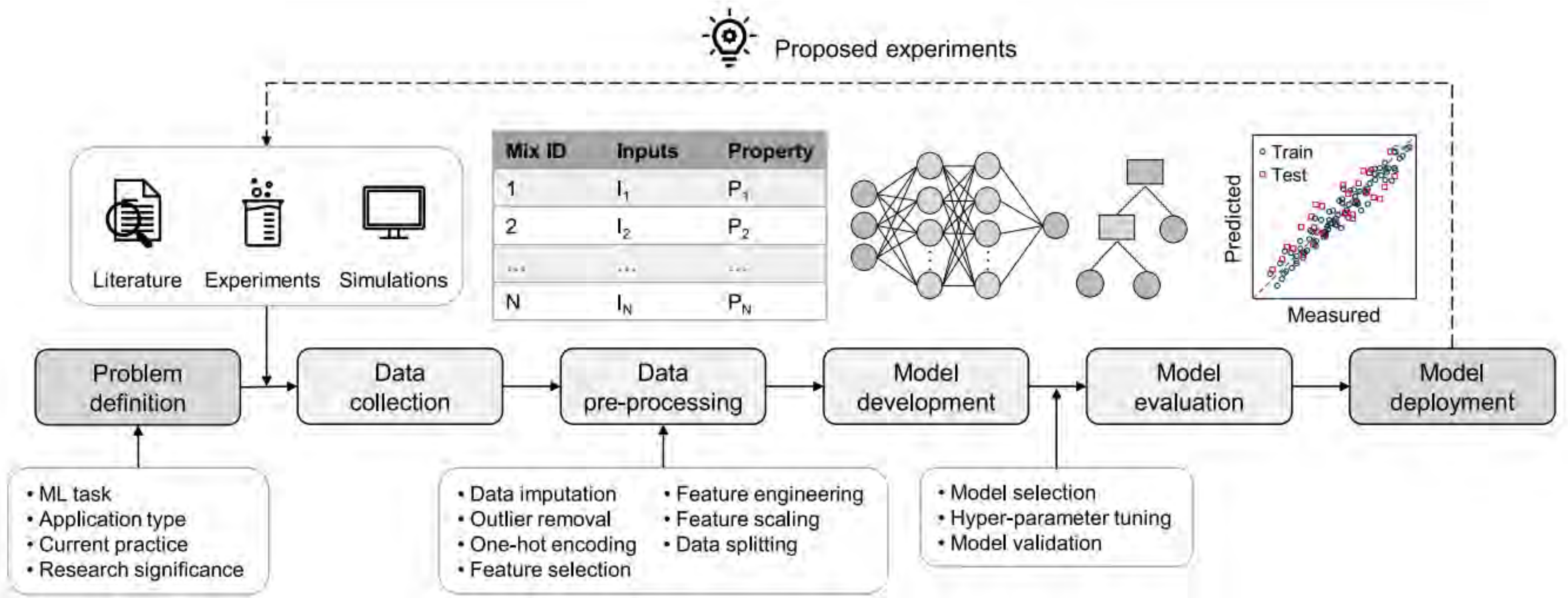
(Reference: Li et al. 2022, Hu et al. 2021, Kazemi 2023)

Advent of AI in Concrete Science and Technology (Cont'd)



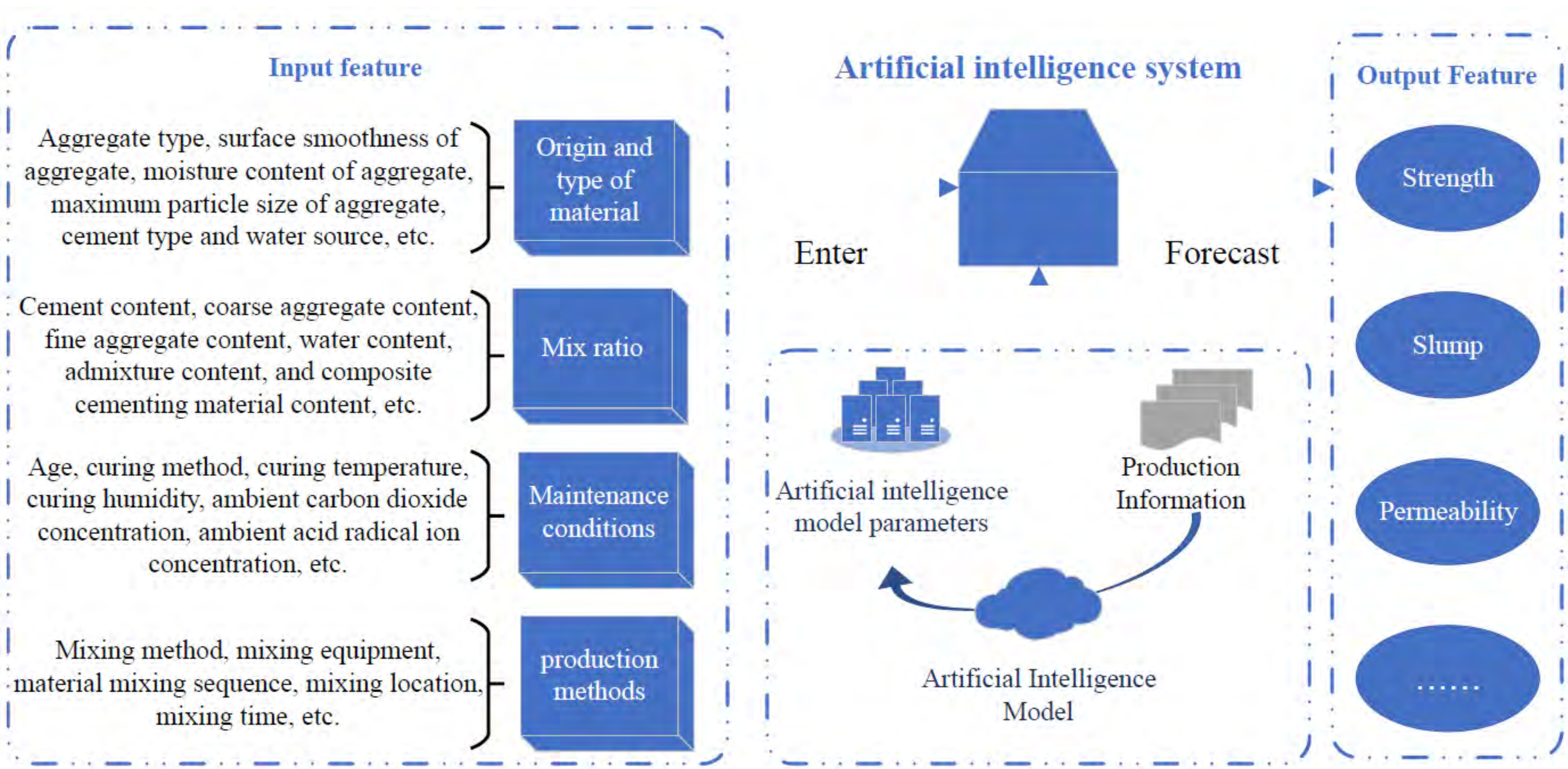
(Reference: Moein et al. 2022)

Advent of AI in Concrete Science and Technology (Cont'd)



(Reference: Li et al. 2022)

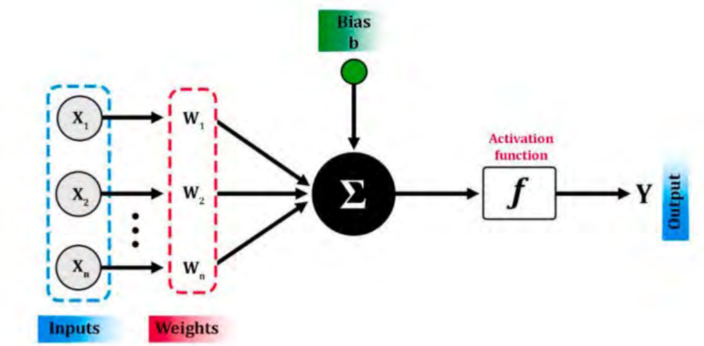
Advent of AI in Concrete Science and Technology (Cont'd)



(Hu et al. 2021)

Artificial Neural Networks (ANNs)

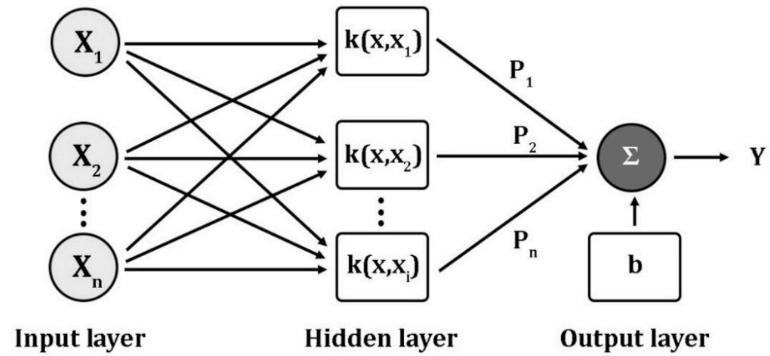
- Prediction of
  - Strength
  - Elastic modulus
  - Flowability
  - Setting behavior
  - Hydration reactions
  - Cement manufacturing process optimization
  - Mix design optimization
  - Pore structure analysis
  - Aggregate shape identification
  - Fiber distribution evaluation
  - Crack detection
  - Quality control for concrete admixture manufacturing or 3D concrete printing
  - Durability prediction such as permeability, Freeze-thaw durability, chloride diffusion, alkali-silica reaction, corrosion, sulfate attack

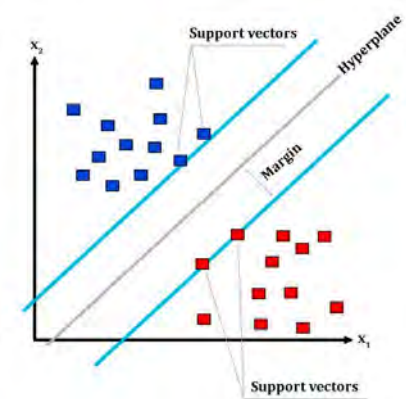


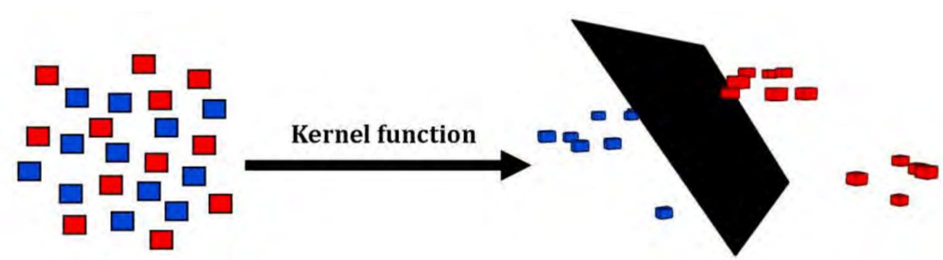
(Reference: [Li et al. 2022](), [Moein et al. 2022]())

Support Vector Machine (SVM)

- Prediction of
  - Strength
  - Elastic modulus
  - Flowability
  - Elastic constant of C-S-H
  - Creep
  - Mix design optimization
  - Identification of fiber failure mode
  - Crack detection
  - Quality control for concrete admixture manufacturing or 3D concrete printing
  - Durability prediction such as permeability, Freeze-thaw durability, chloride diffusion, alkali-silica reaction, corrosion, sulfate attack



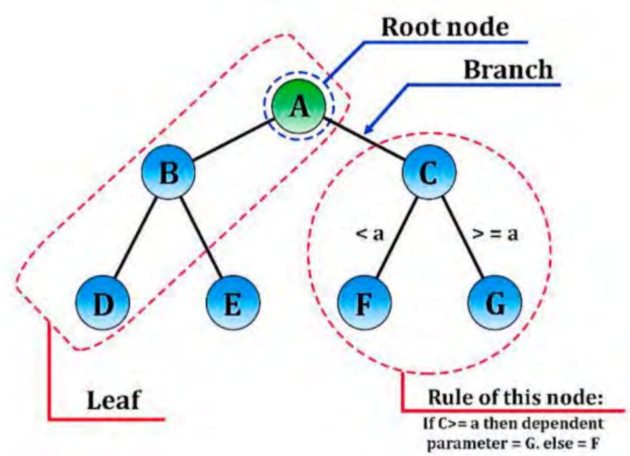




(Reference: [Li et al. 2022](), [Moein et al. 2022]())

Decision Tree (DT)

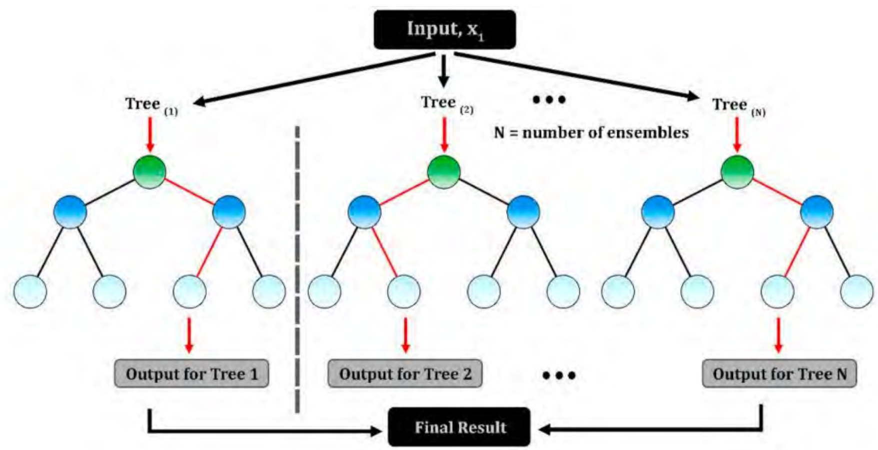
- Prediction of
  - Strength
  - Elastic modulus
  - Flowability
  - Elastic constant of C-S-H
  - Creep
  - Shrinkage
  - Void detection
  - Crack detection
  - Chloride concentration



(Reference: [Li et al. 2022](), [Moein et al. 2022]())

Random Forest (RF)

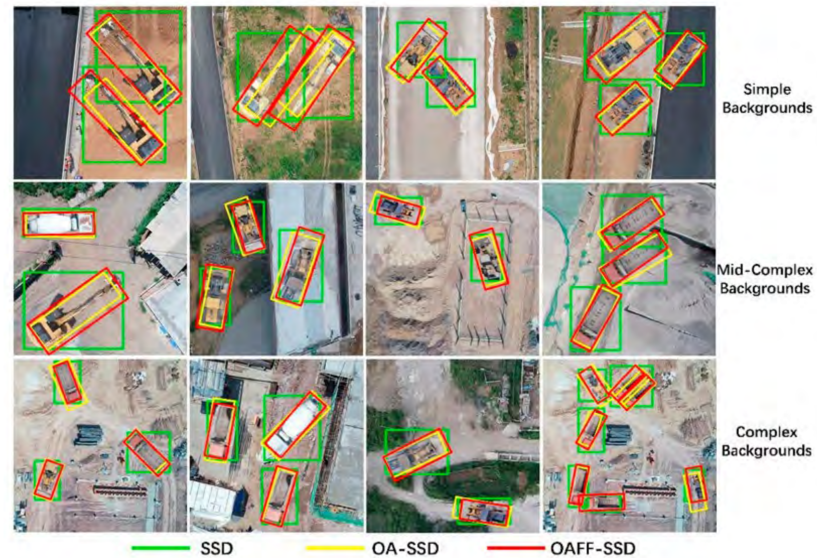
- Prediction of
  - Strength
  - Elastic modulus
  - Flowability
  - Setting behavior
  - Cement hydration kinetics
  - Creep
  - Shrinkage
  - Void detection
  - Crack detection
  - Chloride concentration
  - Thermal properties
  - Mix design optimization
  - Aggregate shape identification

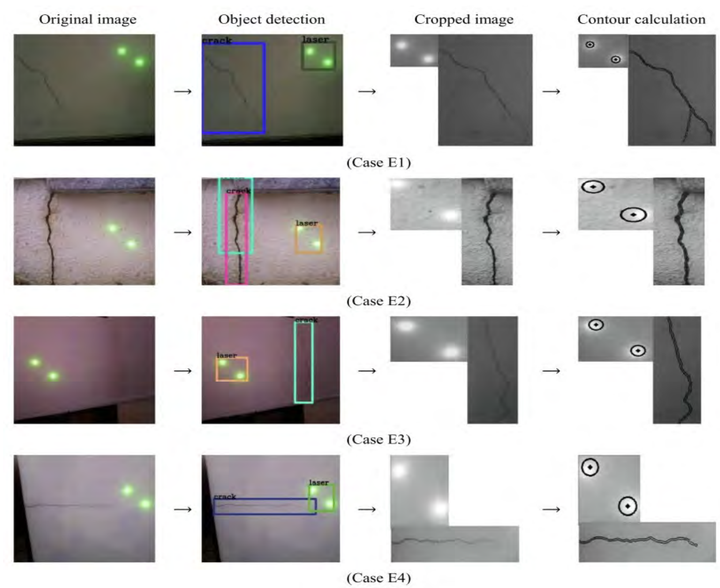


(Reference: Li et al. 2022, Moein et al. 2022)

Deep Learning (DL)

- Equipment tracking in construction sites
- Construction site management
  - Locating workers onsite
  - Detecting worker unsafe behavior
  - Analyzing construction safety
  - Classifying accident reports
  - Detecting worker compliance with PPE
  - Hardhat usage
  - Worker physical loading
  - Detecting structures and information onsite
- Crack detection
  - Detection, classification, and localization of cracks





Outline

- Introduction: Fundamentals of Concrete and Artificial Intelligence (AI)
- Advent of AI in Concrete Science and Technology
- Applications of AI in Concrete Design and Construction
- Case Studies and Success Stories: Dr. Ceylan’s Research on Use of AI for Concrete Pavement Systems
- Summary

Applications of AI in Concrete Design and Construction

- Application types
  - Material characterizations
  - Concrete mix design
  - Quality control and inspection
  - Project management and scheduling
  - Structural optimization
  - Structural condition assessment and health monitoring
  - And many others

Applications of AI in Concrete Design and Construction (Cont'd)

- In concrete technology which deals with the study of concrete materials characterization, fresh and hardened properties, behaviors, and its applications, AI has been used extensively to evaluate, predict and model the properties of fresh, hardening, and hardened concrete

- Not only that, but it has also been applied to optimizing environmentally friendly materials used to replace cement using a prediction technique of the impact of adding these materials, such as fly ash on the performance of concrete

(Reference: Gamil 2023)

Applications of AI in Concrete Design and Construction (Cont'd)

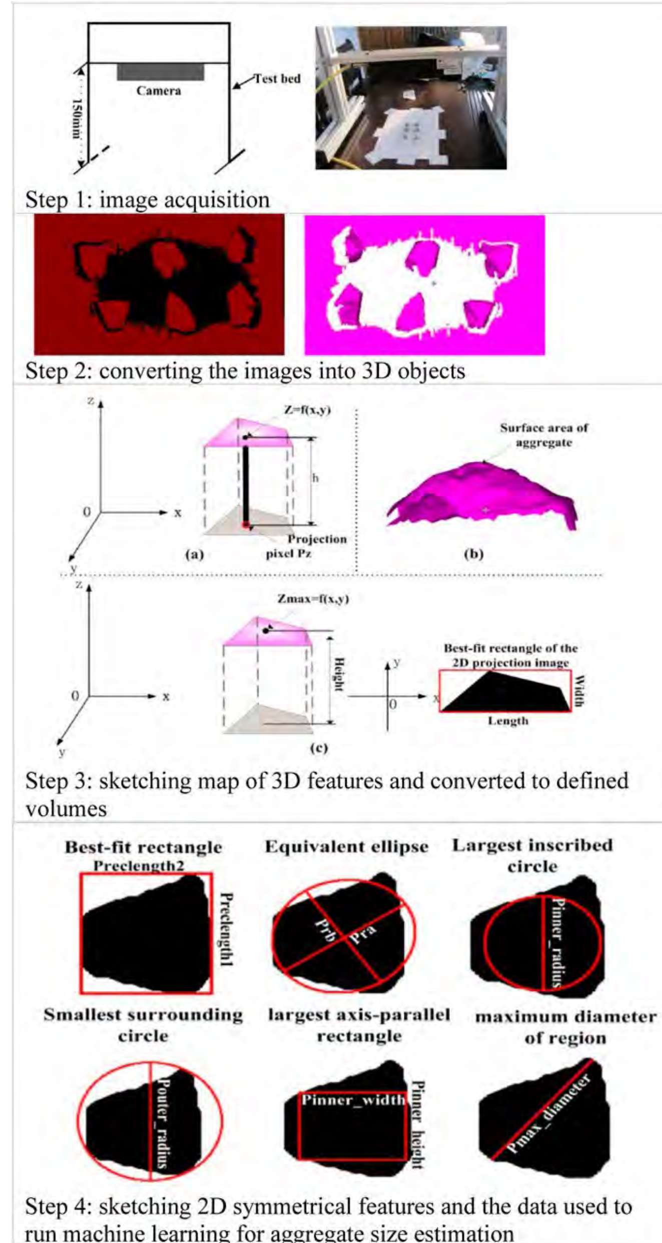
- Areas of AI application in various concrete technologies

Categories	Sub-categories	References application(s)
Materials characterizations	– Particle sizes and shapes – Moisture – Density	Altuhafi et al. (2013), Ohm et al. (2013), Pani and Mohanta (2015), Zheng and Hryciw (2018)
Mix design development	– Proportions – Optimization	Lee et al. (2012), Ziolkowski and Niedostatkiewicz (2019), Nguyen et al. (2020), Kina et al. (2021), Pandey et al. (2021)
Fresh properties	– Slump, slump flow, – Air content, moisture – Fresh concrete density, – Yield stress, – Segregation, bleeding, homogeneity, – Concrete temperature, ambient temperature, – and viscosity.	Öztaş et al. (2006), Mohebbi et al. (2011), Chandwani et al. (2015), Mashhadban et al. (2016), Song et al. (2019), Timur Cihan (2019), Zheng et al., 2019; Unlu (2020), Kina et al. (2021)
Hardening and hardened properties	– Hydration rate through SEM image processing – Strength development (maturity) and characteristic strength – Formwork removal time – Tensile strength	Kim et al. (2004), Yan and Shi, 2010; Atici (2011), Siddique et al. (2011), Dantas et al. (2013), Duan et al. (2013), Naderpour et al. (2018), Cook et al. (2019), Nguyen et al. (2019), Timur Cihan (2019), Abuodeh et al. (2020), Asteris and Mokos (2020), Nguyen et al. (2020), Guzmán-Torres et al. (2021), Su et al. (2021)
Durability	– Chemical attacks, weathering, and abrasion – Carbonation depth – Chloride penetration	Taffese and Sistonen (2017), Alexander and Beushausen (2019), Cai et al. (2020), Feo et al. (2020), Nunez and Nehdi (2021)
Crack detections	– Early crack detection – Failure surface – Cracks propagation (image processing) – The severity of the cracks	Yokoyama and Matsumoto (2017), Bayar and Bilir (2019), Das et al. (2019), Kim et al. (2019), Deng et al. (2020), Okazaki et al. (2020), Wang et al. (2020), Kaur and Singla (2022)

(Reference: Gamil 2023)

Applications of AI in Materials Characterization

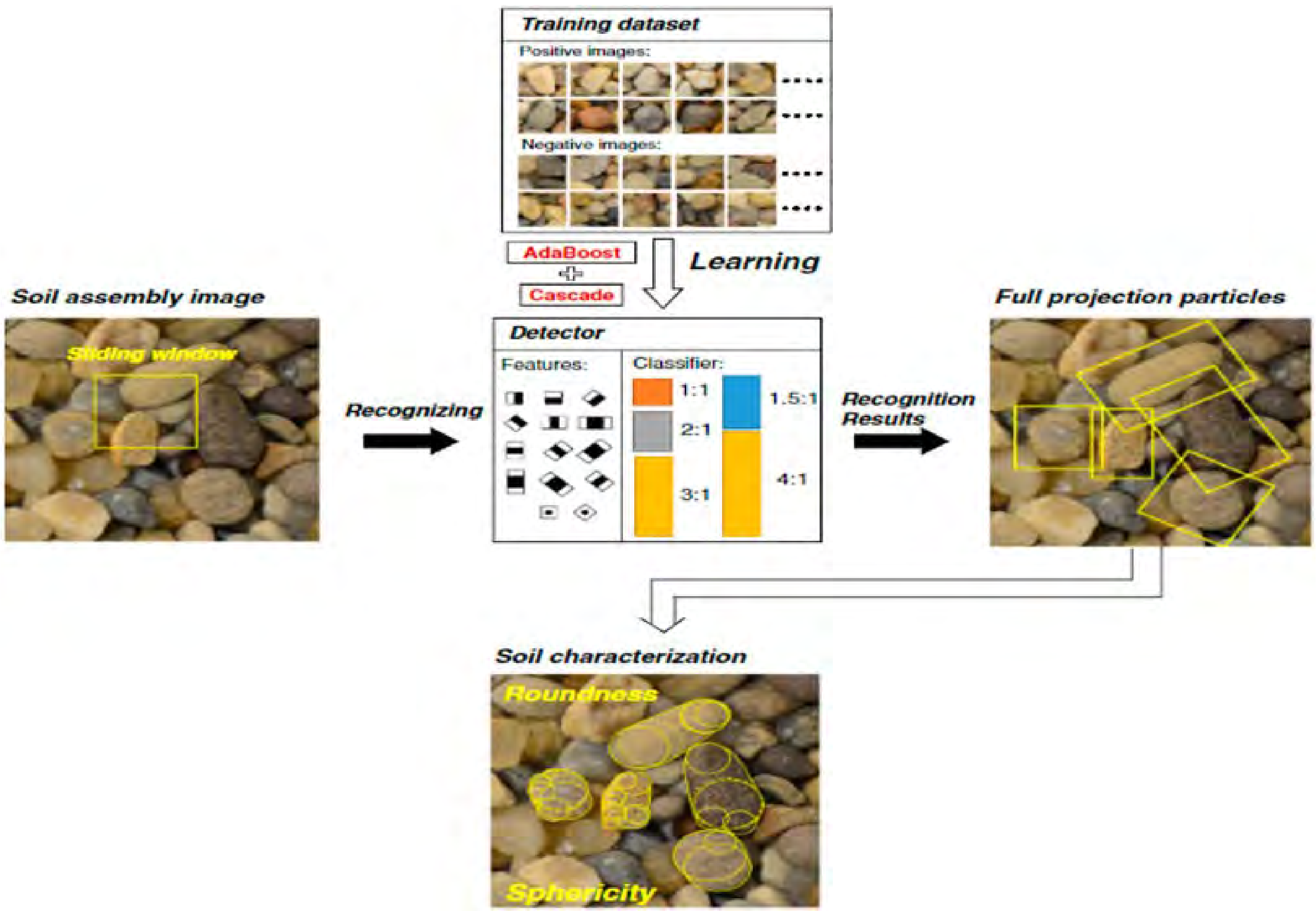
- Importance-based AI feature to define the aggregate size distribution using a measured 3D binocular system
  - Step 1: Image acquisition
  - Step 2: Converting the images into 3D objects
  - Step 3: Sketching map of 3D features and converted to defined volumes
  - Step 4: Sketching 2D symmetrical features and the data used to run machine learning for aggregate size estimation



(Reference: Sun et al. 2021)

Applications of AI in Materials Characterization (Cont'd)

- Method of pattern recognition for shape characterization

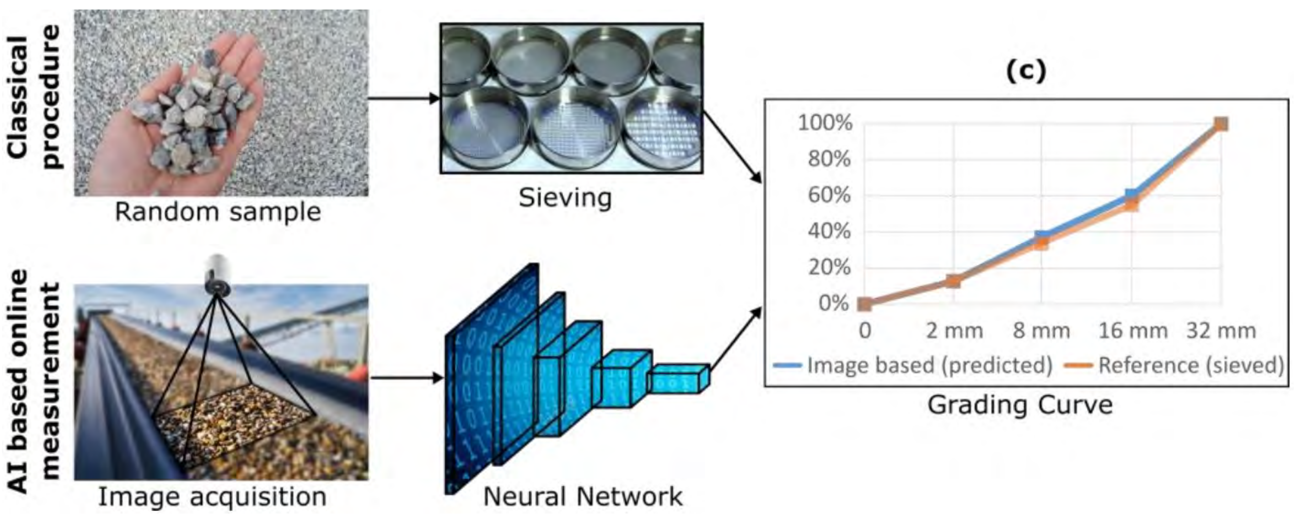


(Reference: Zheng and Hryciw, 2018)

Applications of AI in Materials Characterization (Cont'd)

- Grading curve of the aggregates is usually determined from small random batch-samples
  - Unknown variations of the aggregate's grading curve
    - Increased cement → Increased cost

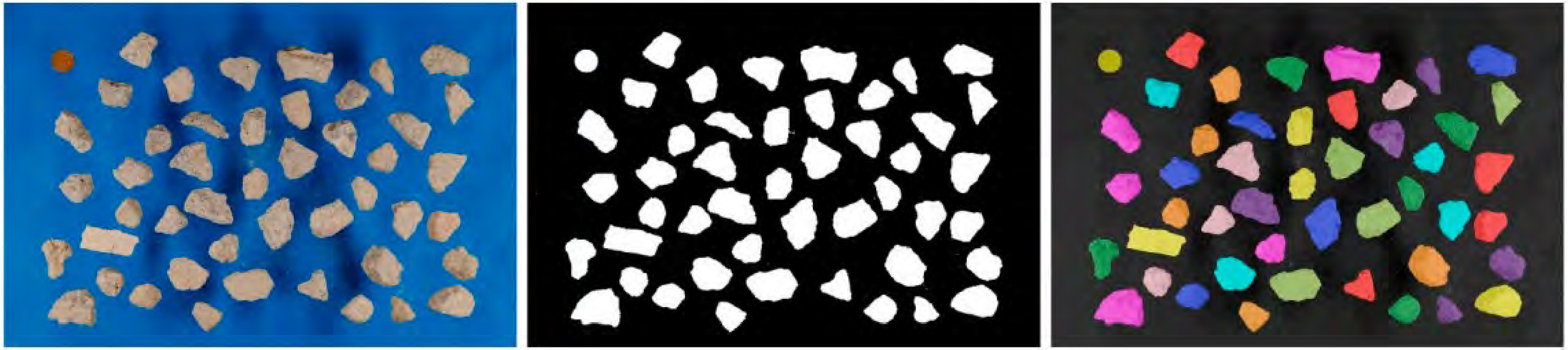
- Cameras tracks the total amount of aggregates used and generate gradation curve based on CNN & image processing



(Reference: Hasit et al. 2022)

Applications of AI in Materials Characterization (Cont'd)

- Determine composition in near real time and in an automated way
- A validation accuracy of 97% for classifying images of grain



(Reference: Hoong et al. 2020)

Applications of AI in Concrete Mix Design

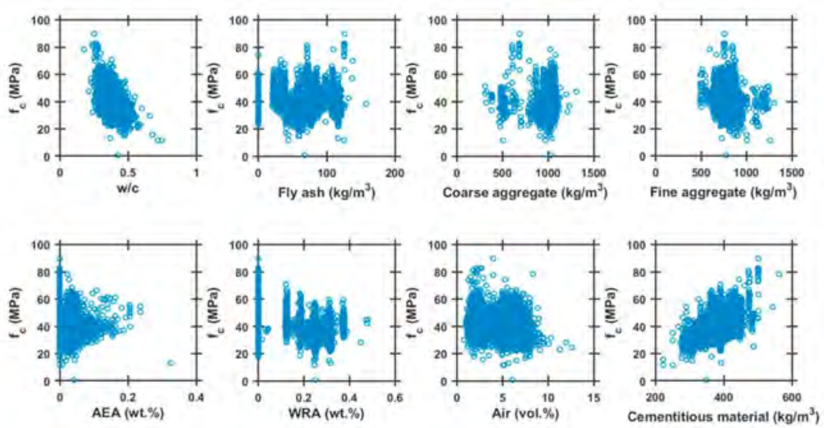
- Development of appropriate mix design is a time-consuming and cost-incurred process

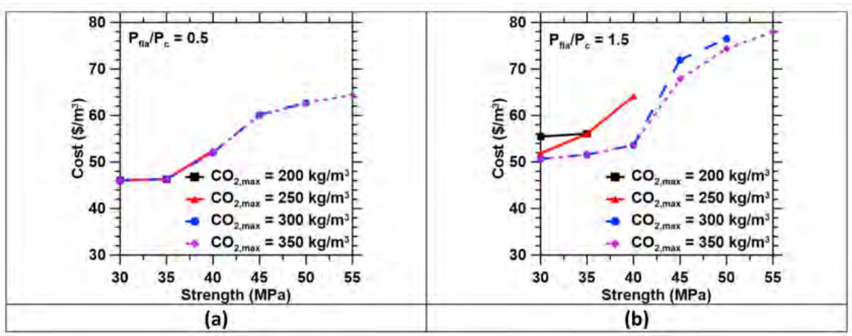
- AI and ML techniques have been used to develop the mix designs based on collective historical data (Esmaeilkhanian et al. 2017, Ziolkowski and Niedostatkiewicz 2019, Chaabene et al. 2020)

- The process utilized historical data to predict the best and wanted mix design with the stipulated performance requirements
  - For example, Ziolkowski and Niedostatkiewicz (2019) used AI and ML to develop a mix design based on extensive databases of concrete recipes
  - Data was used to feed the optimal architecture of neural networks, which resulted into development of an equation enabling the prediction of mix design and compressive strength as a performance indicator

Applications of AI in Concrete Mix Design (Cont'd)

- Predictive models
  - To examine relationships between the mixture design variables and strength
  - To develop an estimate of the (28-day) strength
  - To design optimal concrete mixtures that minimize cost and embodied CO_2

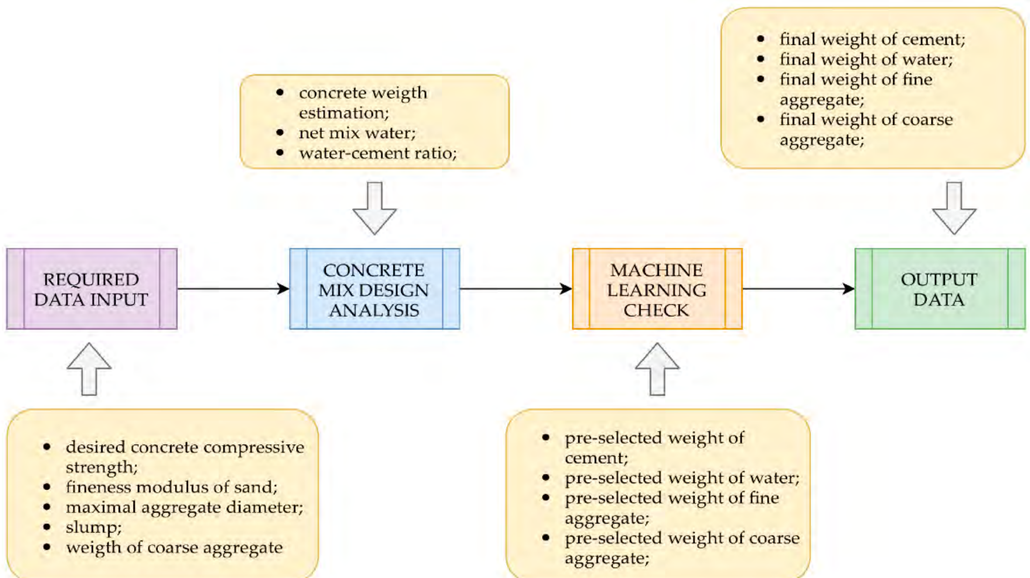




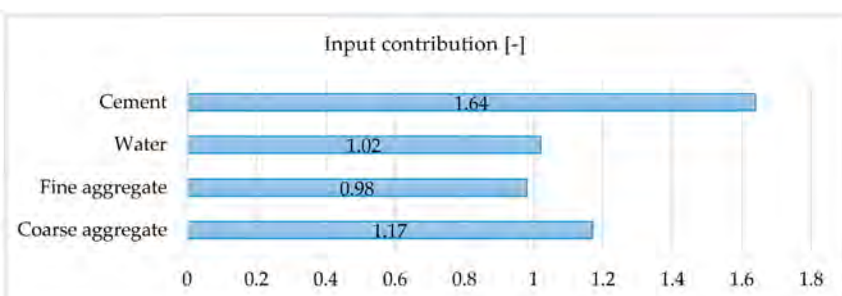
(Reference: Young et al. 2019)

Applications of AI in Concrete Mix Design (Cont’d)

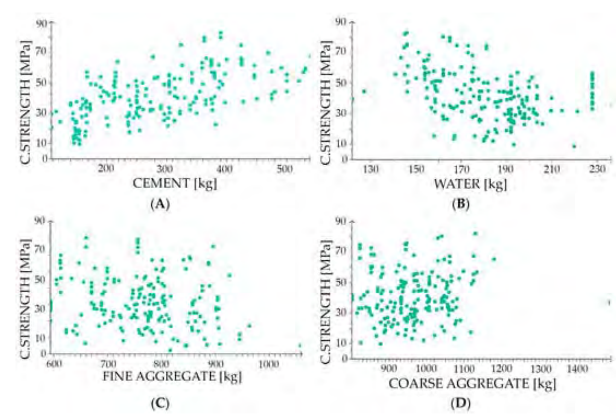
- Ziolkowski and Niedostatkiewicz (2019)



Block diagram of the practical application of machine learning in the concrete mix design



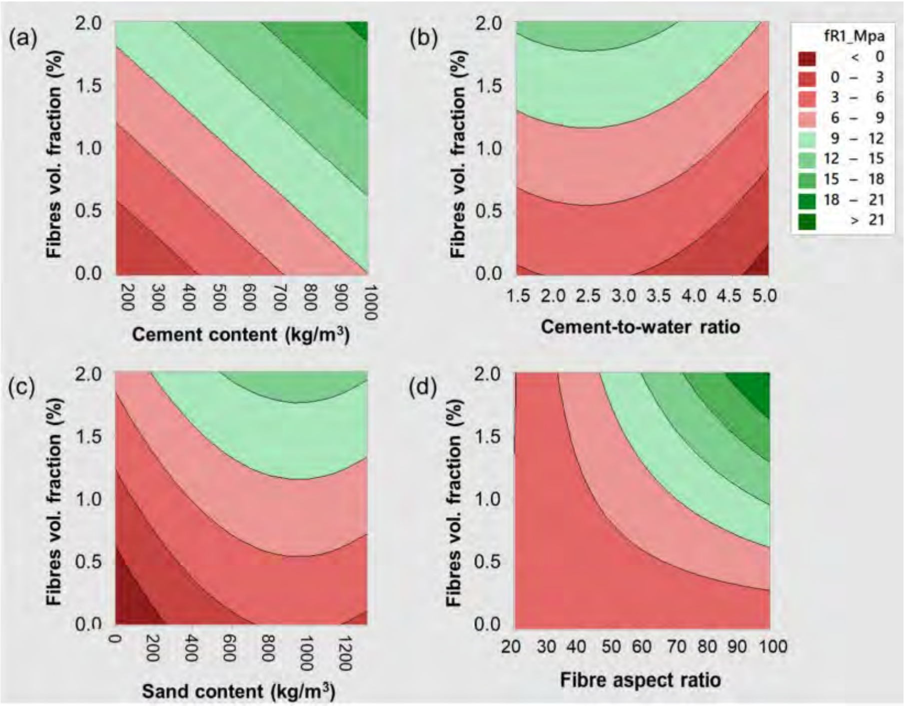
Input contribution



The scatter plots target versus input variable

Applications of AI in Concrete Mix Design (Cont'd)

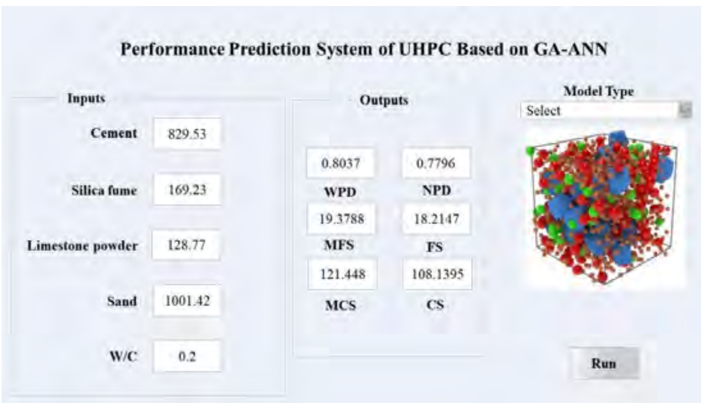
- Proportioning and Optimization of FRC Mixes (OptiFRC)
  - Compiled an exhaustive database of FRC mix proportioning and their properties
    - To analyze their variability using data mining techniques
    - To develop robust models for estimating the residual flexural strength
    - To implement these developments in an optimization tool

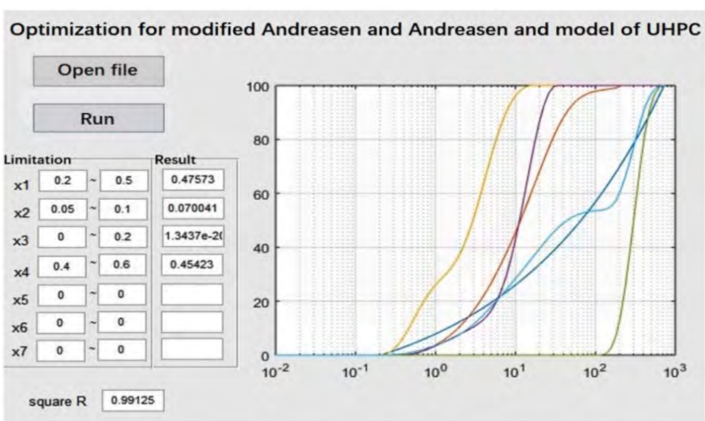


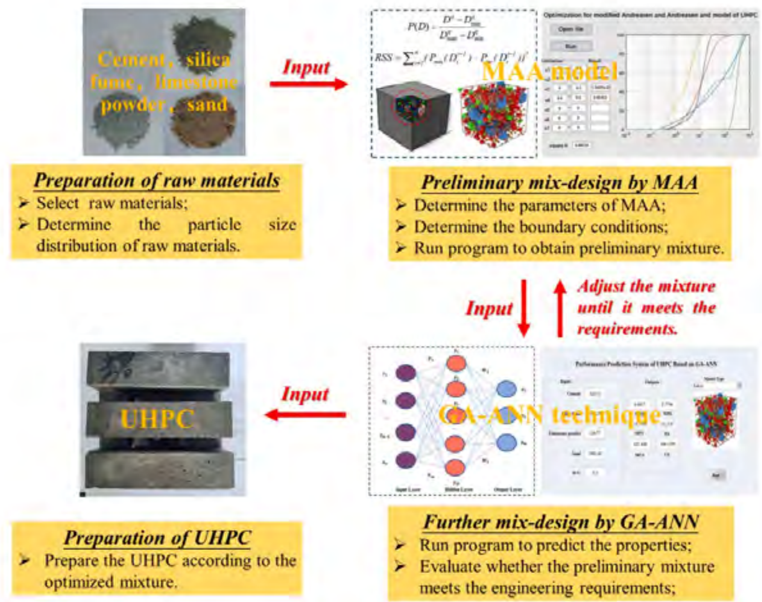
(Reference: Emilio Garcia-Taengua. 2020)

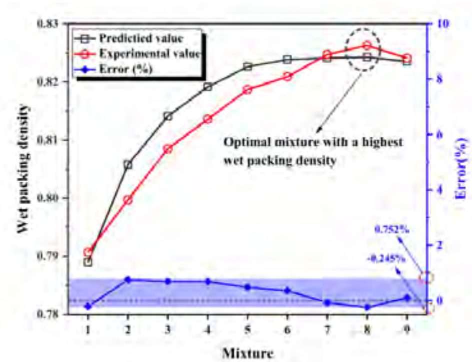
Applications of AI in Concrete Mix Design (Cont'd)

- UHPC with dense particle packing system can be developed by the combined use of MAA model and Genetic Algorithm based Artificial Neural Network









(Reference: Fan et al. 2021)

Applications of AI in Quality Control and Inspection

- Offline quality inspection of fresh concrete
  - Uses empirical test methods
  - On small batch samples of the concrete
  - Limited control of the concrete properties remains possible

- Online quality assessment during the mixing process enables
  - Real-time control of the concrete properties
  - Prompt reaction on potential deviations from the target properties

- Current technology measures the dynamic viscosity only
  - Coarse consistency estimations based on the electrical energy consumption of the mixer
  - Not sufficient for a precise derivation of the complex rheological properties of fresh concrete
    - Yield stress
    - Plastic viscosity
    - Thixotropy
    - Sedimentation and bleeding behavior or setting behavior

- Deep learning can be developed based on 3D image data of the flowing concrete in the mixer to produce values for viscosity and yield stress
  - Adjust the concrete towards its target rheological properties

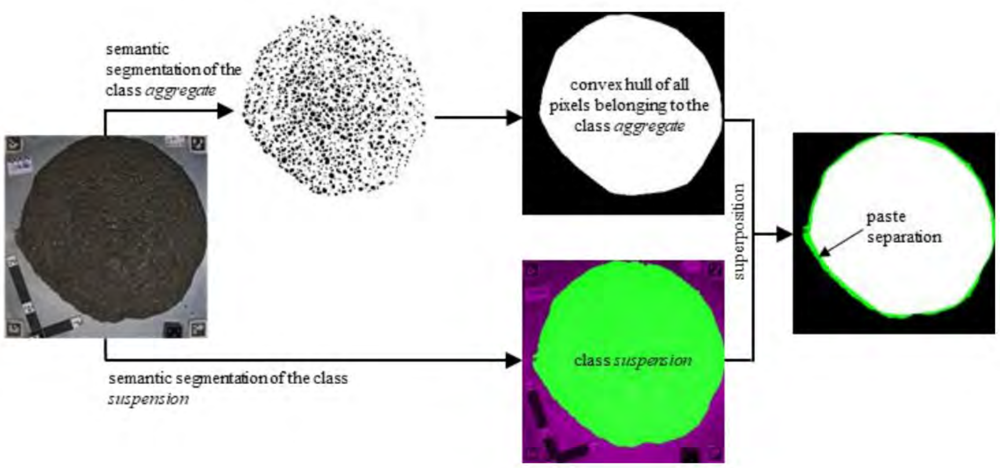
(Reference: Hasit et al. 2022)

Applications of AI in Quality Control and Inspection (Cont'd)

- Fast determination of the fresh concrete properties on the construction site is required
  - Current techniques
    - Correlating the energy consumption for rotating the mixing drum of a truck mixer to values obtained by rheometer tests
    - Using a concrete mixing truck itself as a rheometer
  - Substantial technical modifications on the mixing truck required

- Batch-based methods such as the slump or slump flow test are predominant
  - Surface topography and other surface features of the spread out fresh concrete yield an abundance of additional information

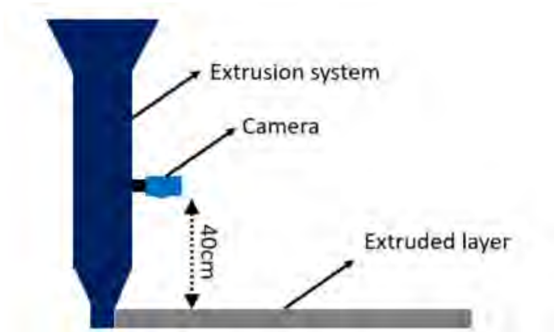
- Photogrammetric computer vision and CNN based algorithms, can correlate optical patterns with concrete rheological properties
  - Actual composition can be derived from a single image of the slump cake

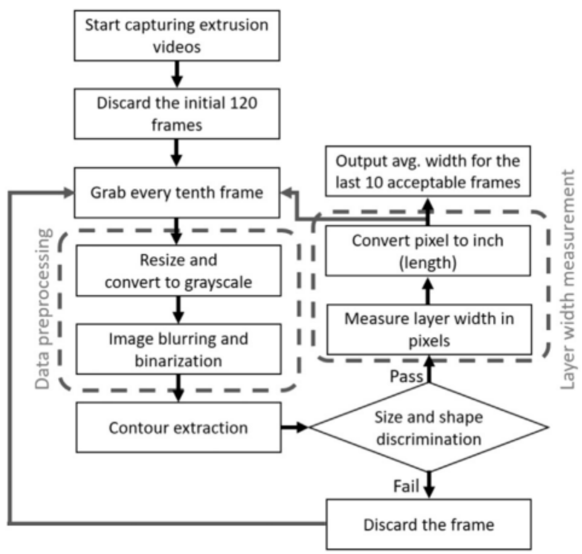


(Reference: Hasit et al. 2022)

Applications of AI in Quality Control and Inspection (Cont'd)

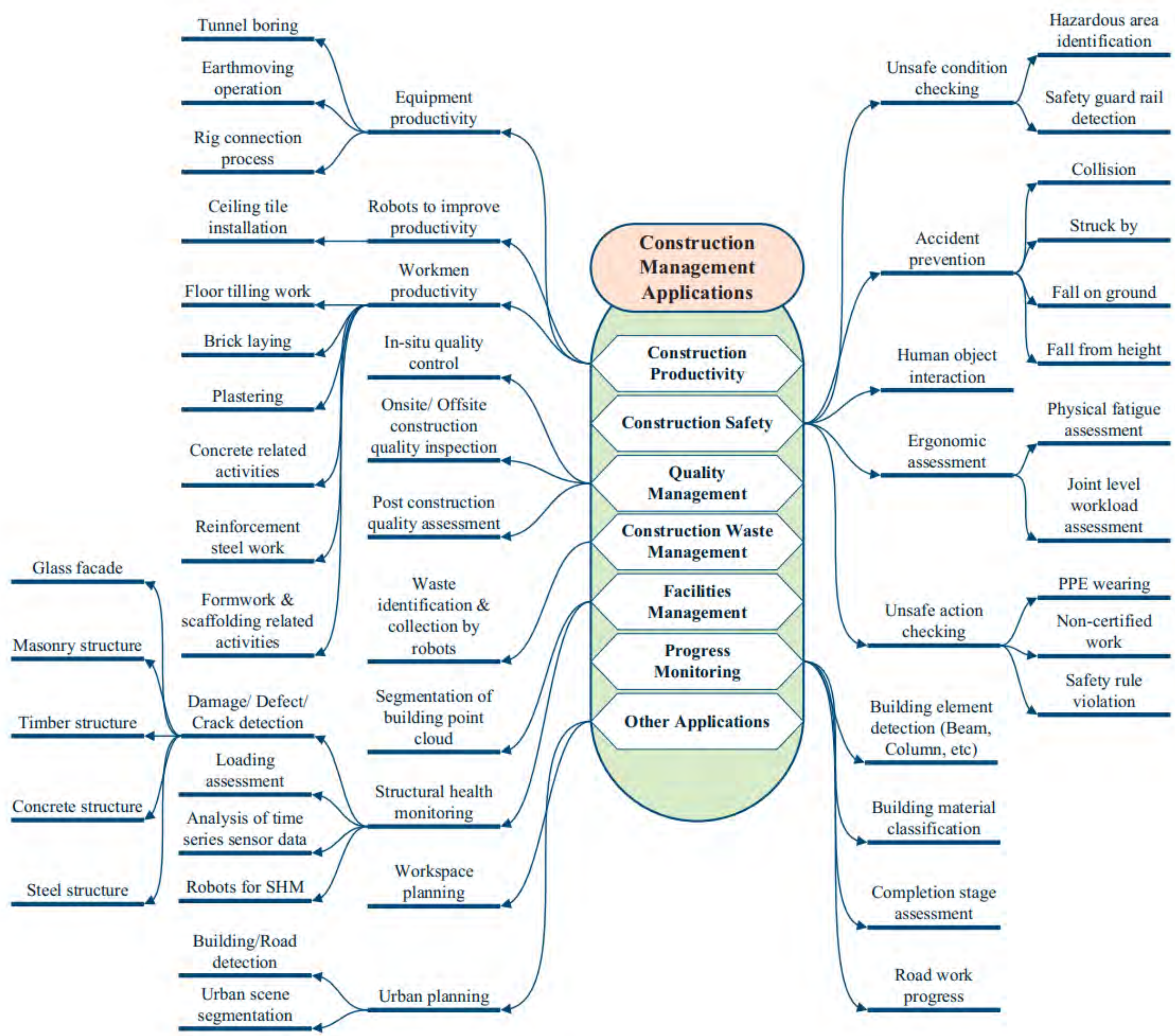
- Computer vision for real-time extrusion quality monitoring and control in robotic construction
- Automatically adjust the extrusion rate based on the vision system feedback
- Self-regulating extrusion system able to continuously print layers of acceptable dimensions using any printable mixture, without the need for prior calibration and despite some mixture rheology variations





(Reference: Kazemian et al. 2022)

Applications of AI in Project Management and Scheduling



AI-based visual data analytics applications in Project management

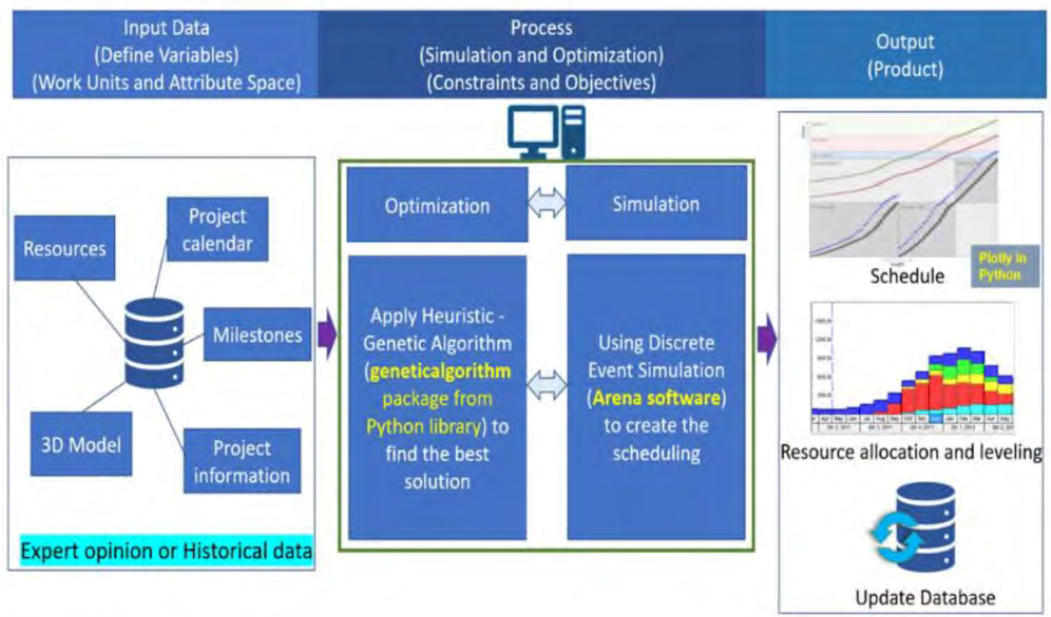
(Reference: Pal and Hsieh. 2021)

Applications of AI in Project Management and Scheduling (Cont'd)

- Common modeling methods for construction planning
  - Linear scheduling (LS)
  - Critical path method (CPM)
  - Discrete-event simulation (DES)

- When the constraints and dimensionality of a planning problem increase, traditional methods are cumbersome and struggle to accurately reflect decision options

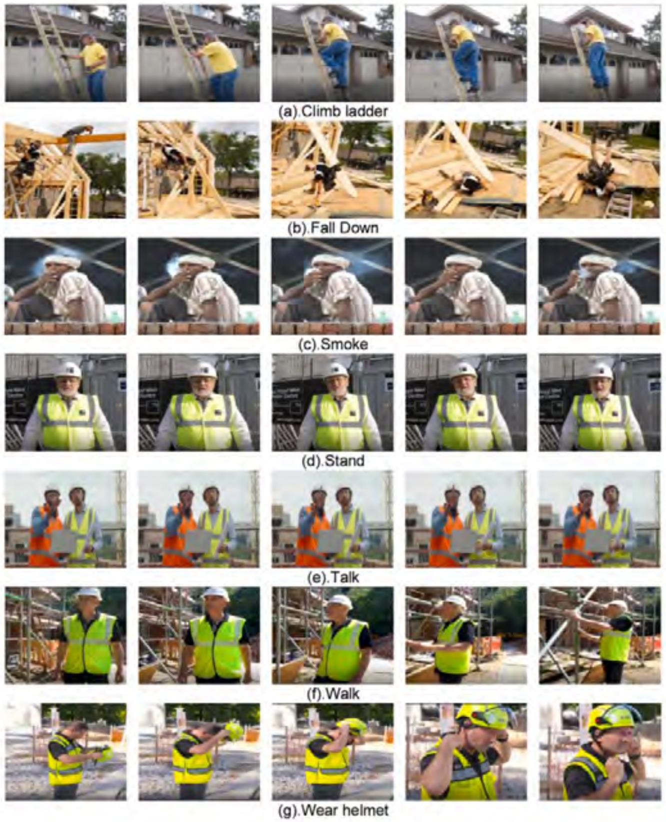
- Deep learning artificial intelligence (AI) methods can more rapidly review and recommend more planning options for scheduling complex construction projects



(Reference: Hatami et al. 2021)

Applications of AI in Project Management and Scheduling (Cont'd)

- AI model and video dataset for unsafe action identification in projects

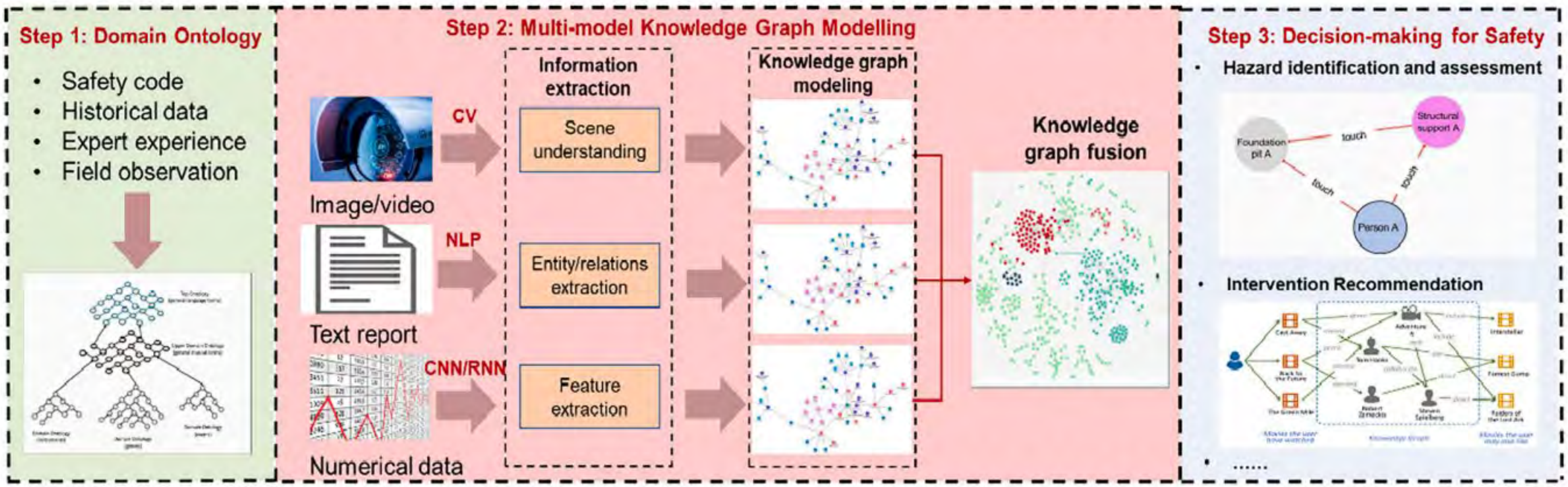


Sample frames for seven action classes of dataset

(Reference: Yang et al. 2023)

Applications of AI in Project Management and Scheduling (Cont'd)

- AI-based data analytics for safety in concrete construction

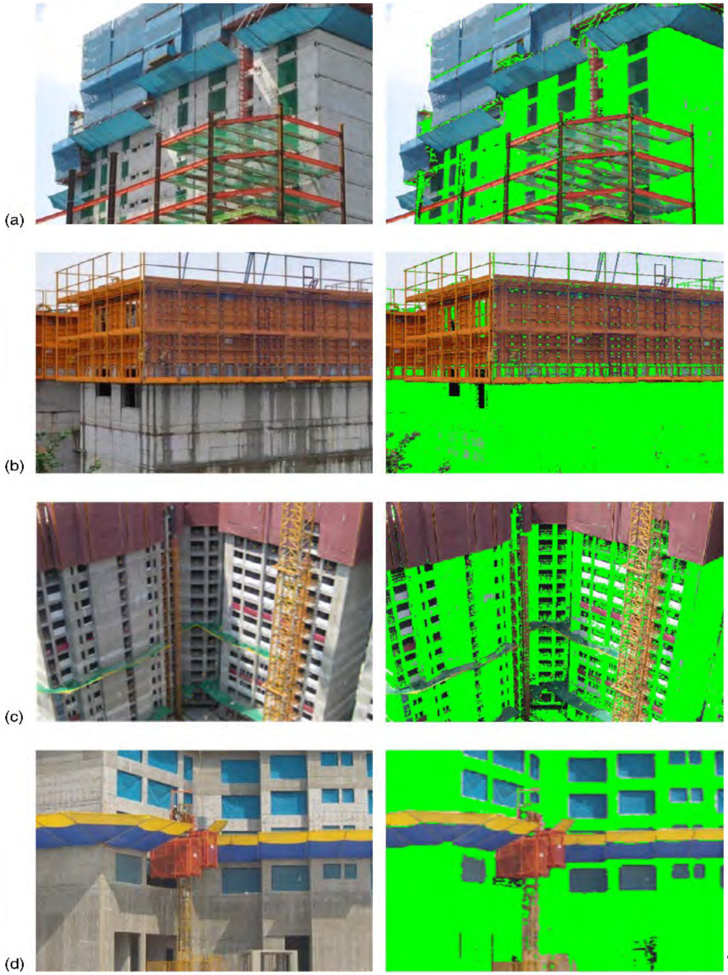


(Reference: Liu et al. 2022)

Applications of AI in Project Management and Scheduling (Cont'd)

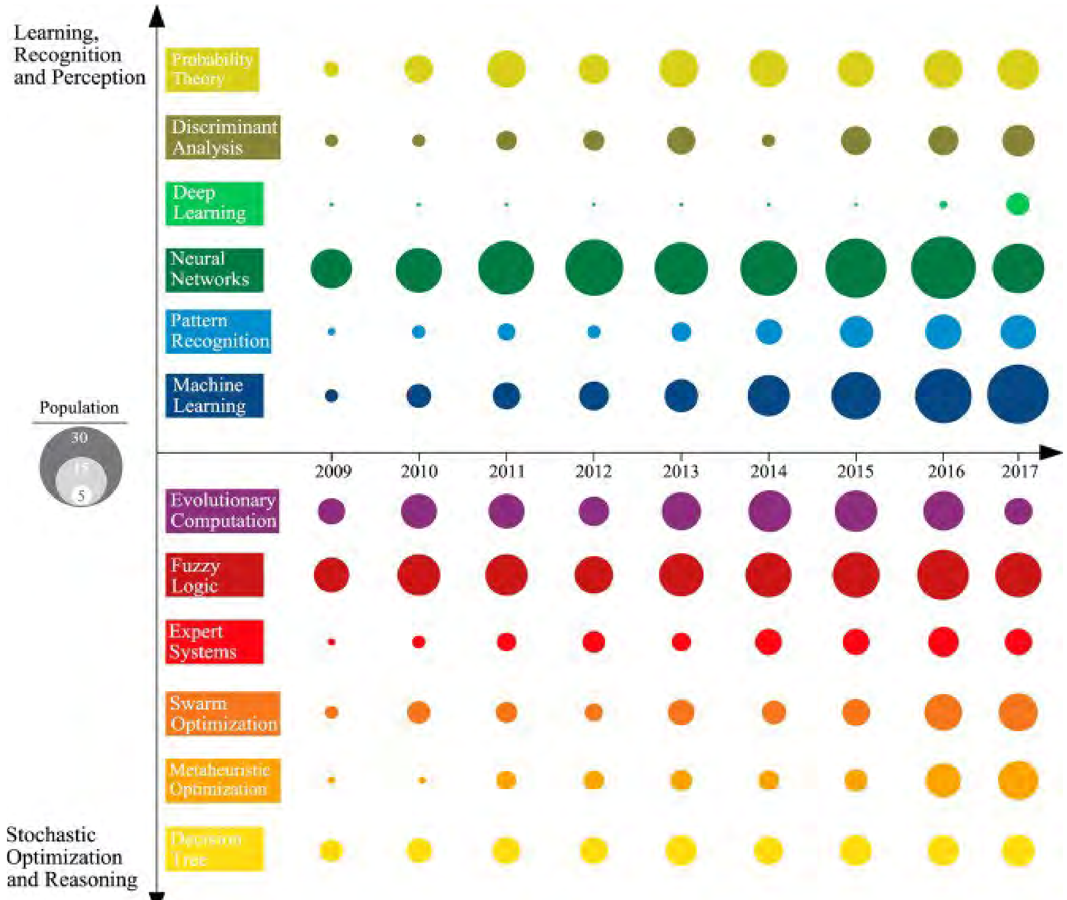
- AI has been used for concrete structural component detection
- For example, Son et al. (2012) used AI and ML to detect concrete on-site using automated color model images with neural networks, and that helped to measure the construction process and monitor the structural health

Construction-site images (left) V.S. AI and ML-based concrete detection results (right)



Applications of AI and ML in Concrete Structural Design

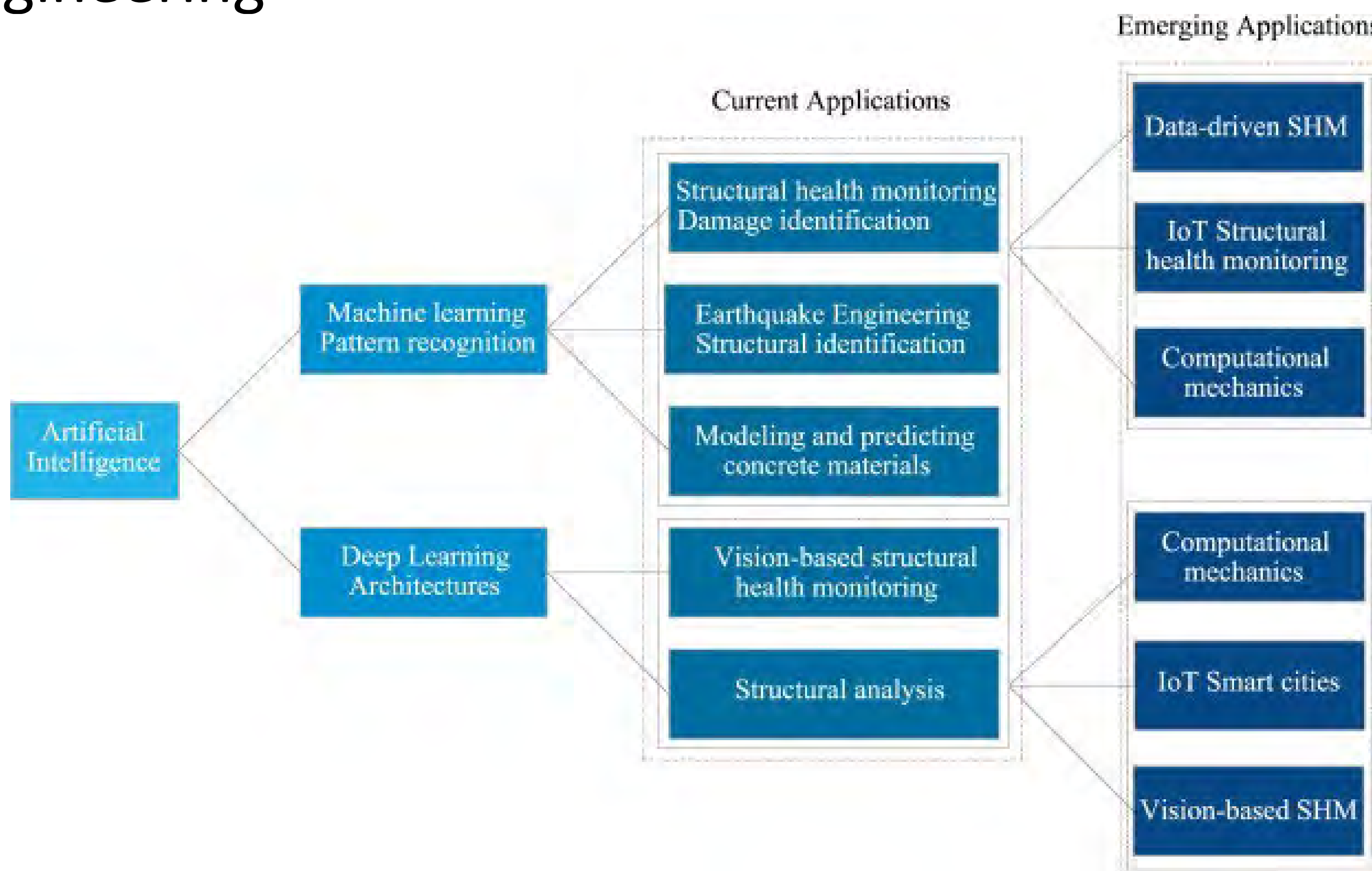
- Research publications on the use of different AI branches in structural engineering



(Reference: Salehi and Burgueño 2018)

Applications of AI and ML in Concrete Structural Design (Cont'd)

- Applications of AI, ML, and DL in concrete structural engineering



(Reference: Salehi and Burgueño 2018)

Applications of AI and ML in Concrete Structure Health Monitoring

- In structural health monitoring, image processing techniques (IPTs) are mainly used to process images to extract defect features, such as cracks on concrete and steel surfaces

- Vision-based autonomous detection of concrete surface defects is significant for efficient maintenance of infrastructures

- For example, Zhang et al. (2017) proposed a Convolutional Neural Network (CNN)-based architecture, named as CrackNet, for the automatic detection off cracks

Applications of AI and ML in Concrete Structure Health Monitoring (Cont'd)

- Typical testing images correctly classified by CrackNet (Zhang et al. 2017)

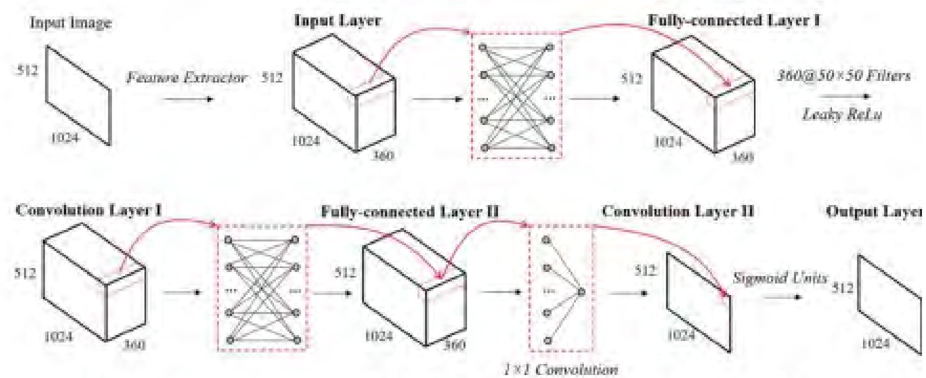
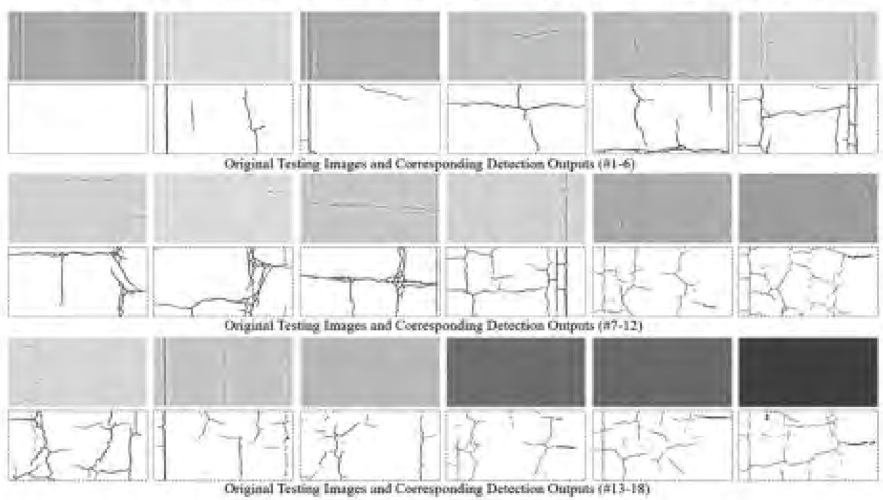
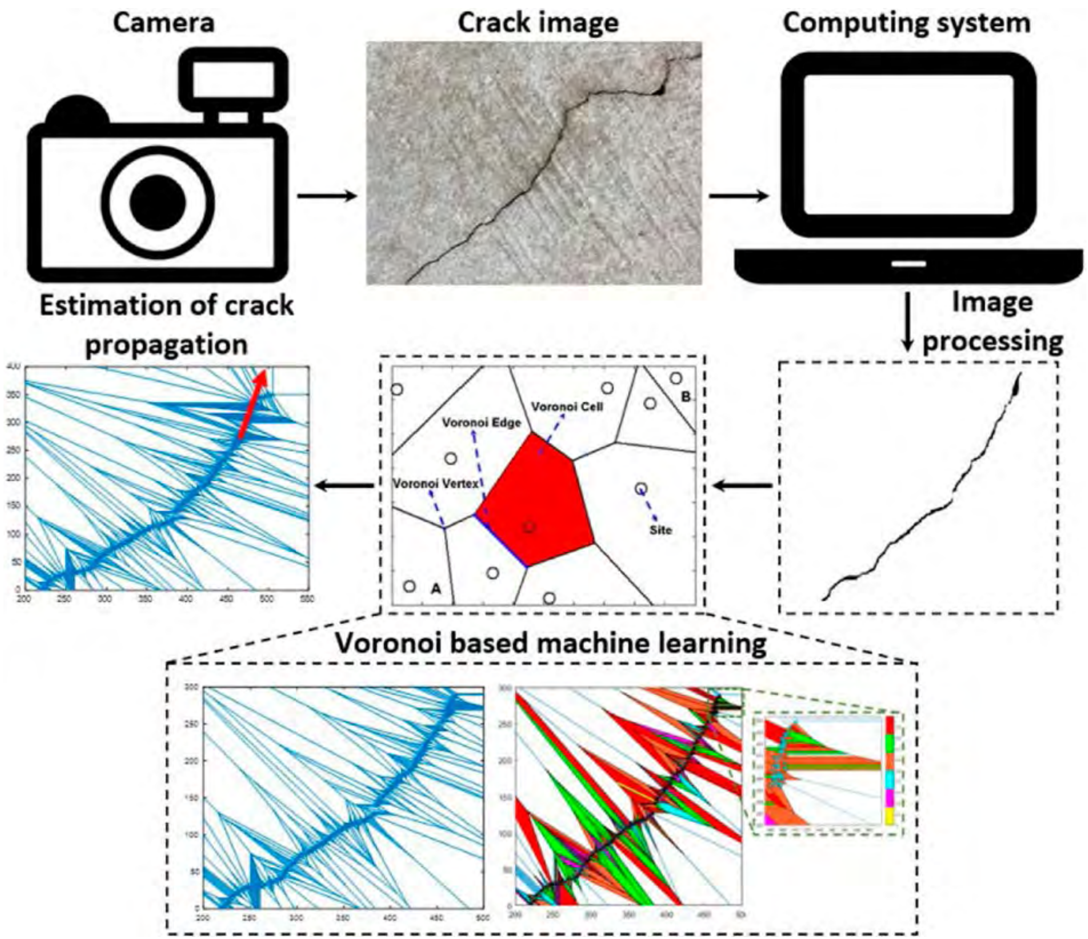


Figure 7: Architecture of CrackNet [Zhang, Wang, Li et al. (2017)]

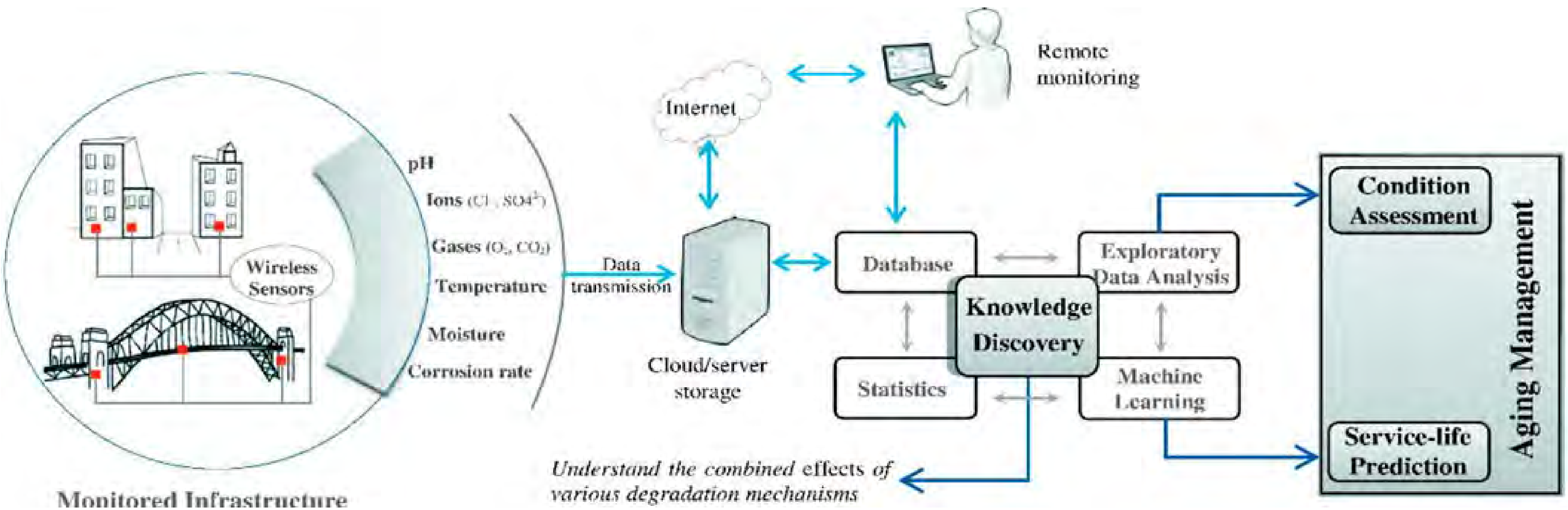


- ML method for crack pattern and propagation detection (Bayar and Bilir 2019)



Applications of AI and ML in Assessment of Service Life

- Assessment of durability and service life of reinforced structure



(Reference: Taffese and Sistonen, 2017)

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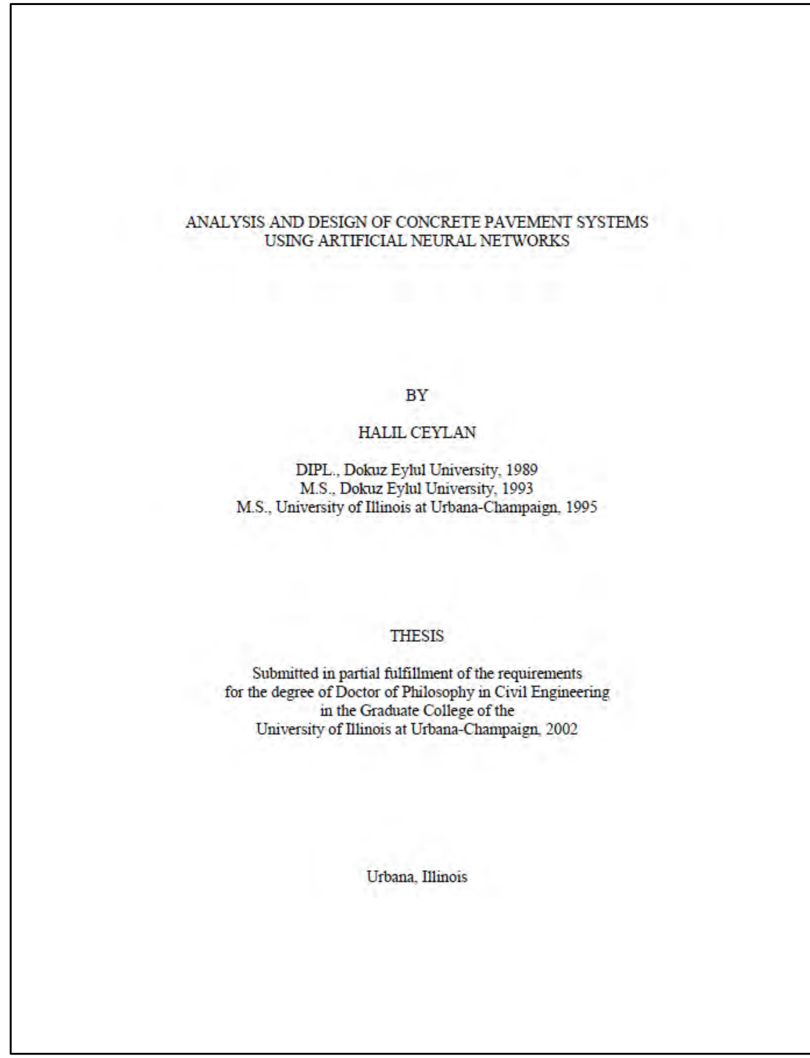
- Summary

Ceylan's Ph.D. Dissertation in 2002

- Supervised by Professors Erol Tutumluer and Ernest J. Barenberg at the University of Illinois at Urbana Champaign (UIUC)

- Professor Jamshid Ghaboussi of University of Illinois, referred to my Ph.D. research accomplishment as "***the first ever successful application at this scale of using Artificial Neural Networks (ANNs) as surrogate structural analysis models to replace complex and sophisticated finite element solutions***."


ANALYSIS AND DESIGN OF CONCRETE PAVEMENT SYSTEMS
USING ARTIFICIAL NEURAL NETWORKS

BY

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THESIS

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in the Graduate College of the
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Dr. Ceylan's Research on Use of AI for Concrete Pavement Systems

- Dr. Ceylan's early research at the UIUC in 2000s and the continuation of that work at ISU has provided a significant basis for the introduction of AI and ML techniques to the analysis and design of concrete pavement systems, including

  – Analysis and design of concrete pavement systems using ANNs
  – Nondestructive structural assessment of concrete pavements using ANNs
  – Implementing a multiple-slab response model for top-down cracking mode in rigid airport pavements
  – AI for predicting PCC overlay performance
  – Development of Iowa Pavement Analysis Technique (IPAT)
  – Use of Small Unmanned Aircraft Systems (sUAS) and ML/DL for Airport pavement inspection and rating
  – Use of AI for predicting concrete compressive strength
  – Several of Dr. Ceylan's ANN models are embedded in the MEPDG/ AASHTOWare Pavement ME Design software system

Analysis and Design of Concrete Pavement Systems Using ANN

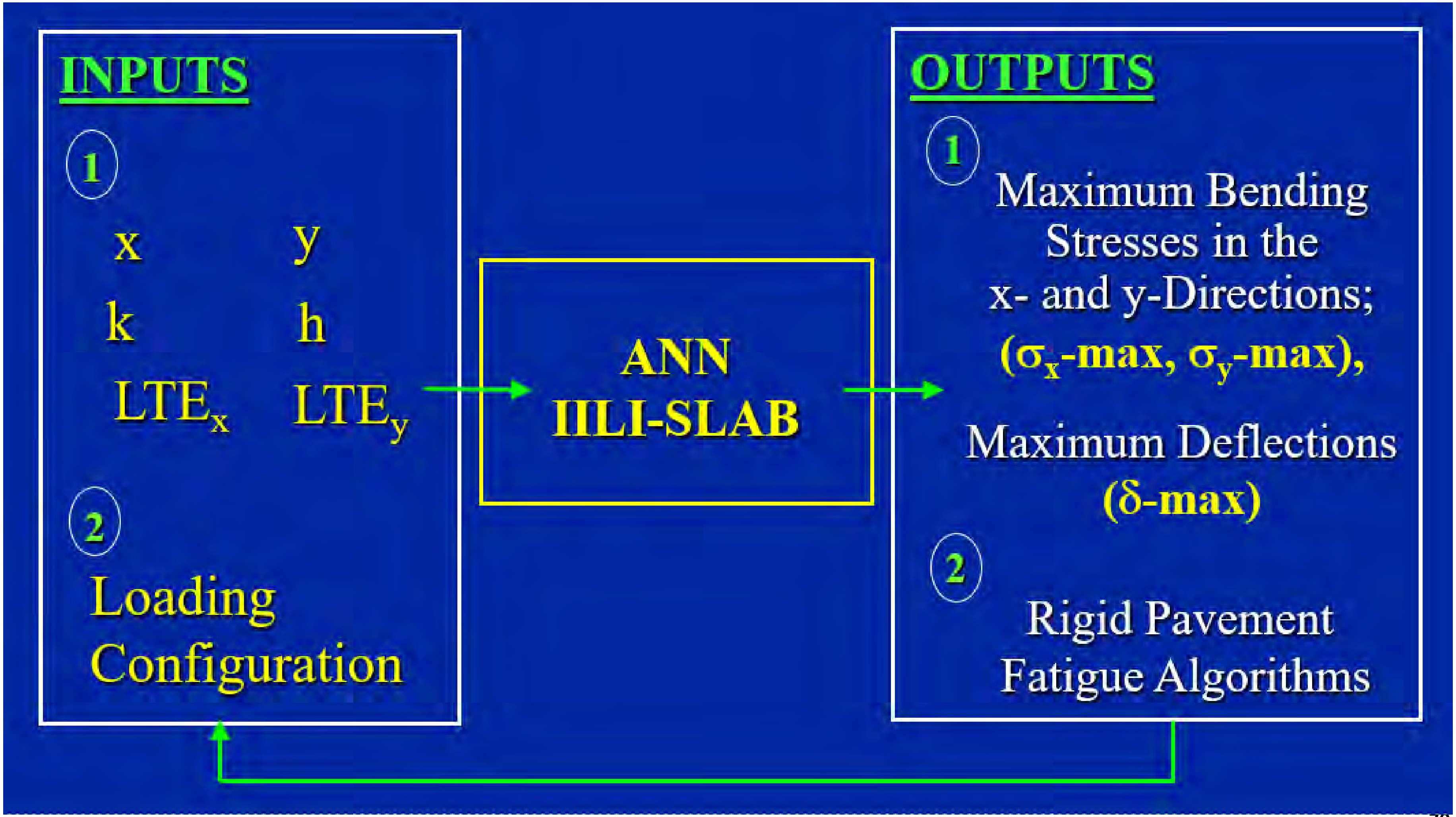
- Objectives
  - Develop an easy-to-use ANN-based concrete pavement analysis toolbox for routine practical design (Mechanistic – Empirical Based Design Methodology)
  - Employ ANNs as structural models to simulate sophisticated finite element (FE) analyses

Analysis and Design of Concrete Pavement Systems Using ANN (Cont'd)

- Methodology
  - Train ANN models to solve for concrete slab stresses and deflections Under:
    - Various standard aircraft gear configurations, including B-777
    - Multiple wheel loadings for general gear configurations
    - Climatic & simultaneous loadings

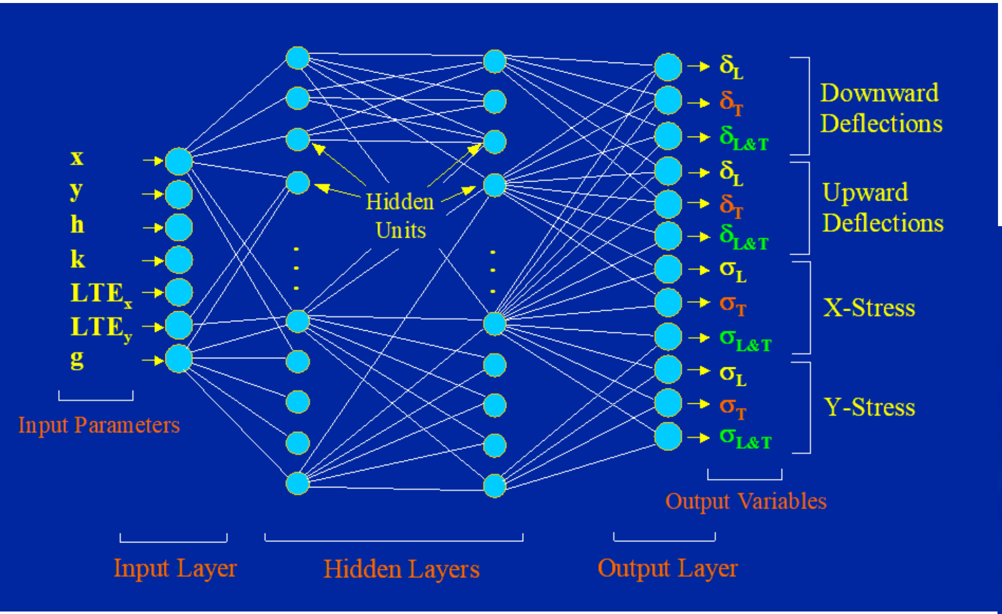
Analysis and Design of Concrete Pavement Systems Using ANN (Cont'd)

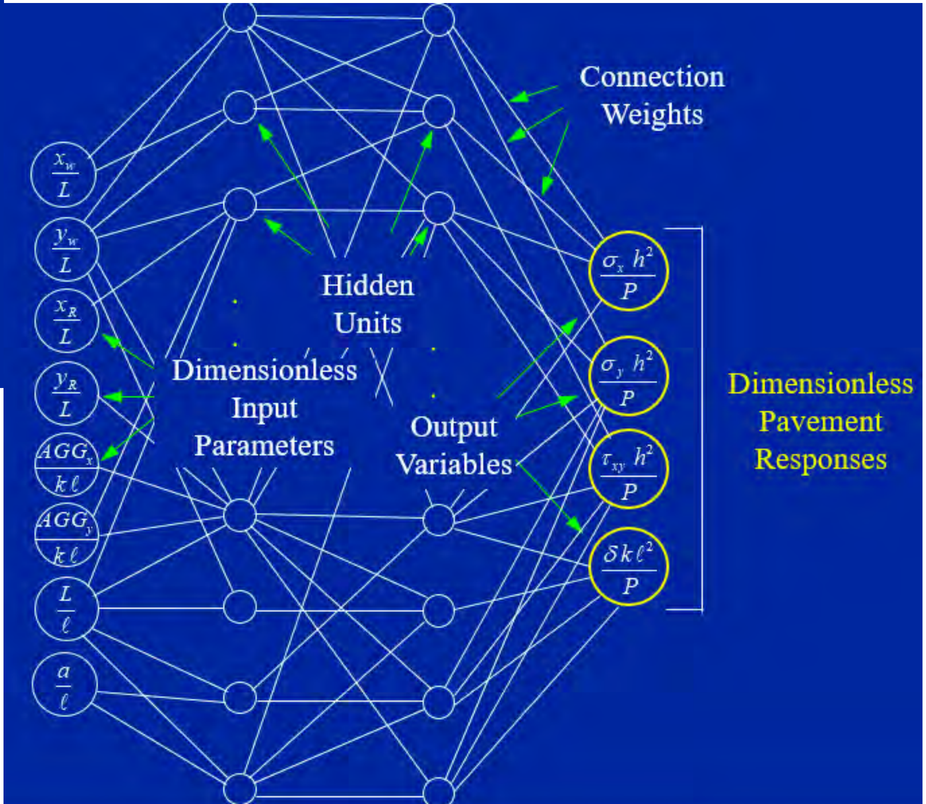
- Graphical representation of ANN toolbox concept



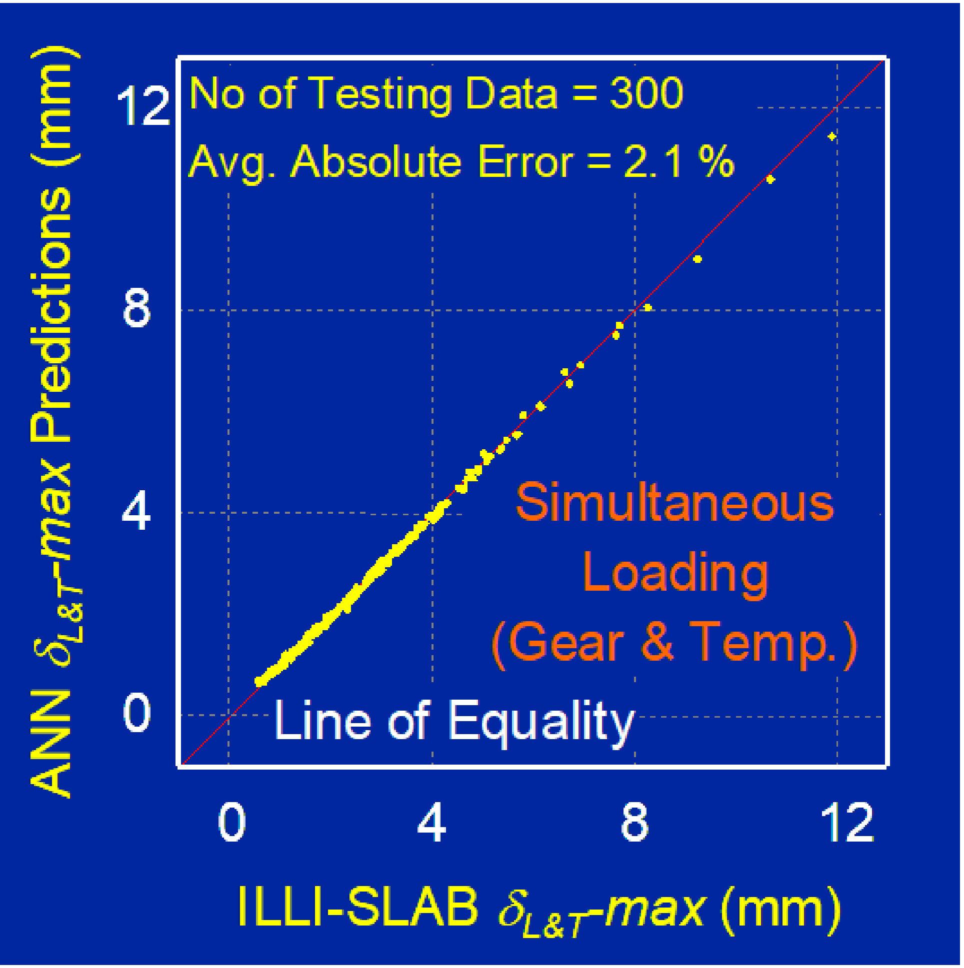
Analysis and Design of Concrete Pavement Systems Using ANN (Cont'd)

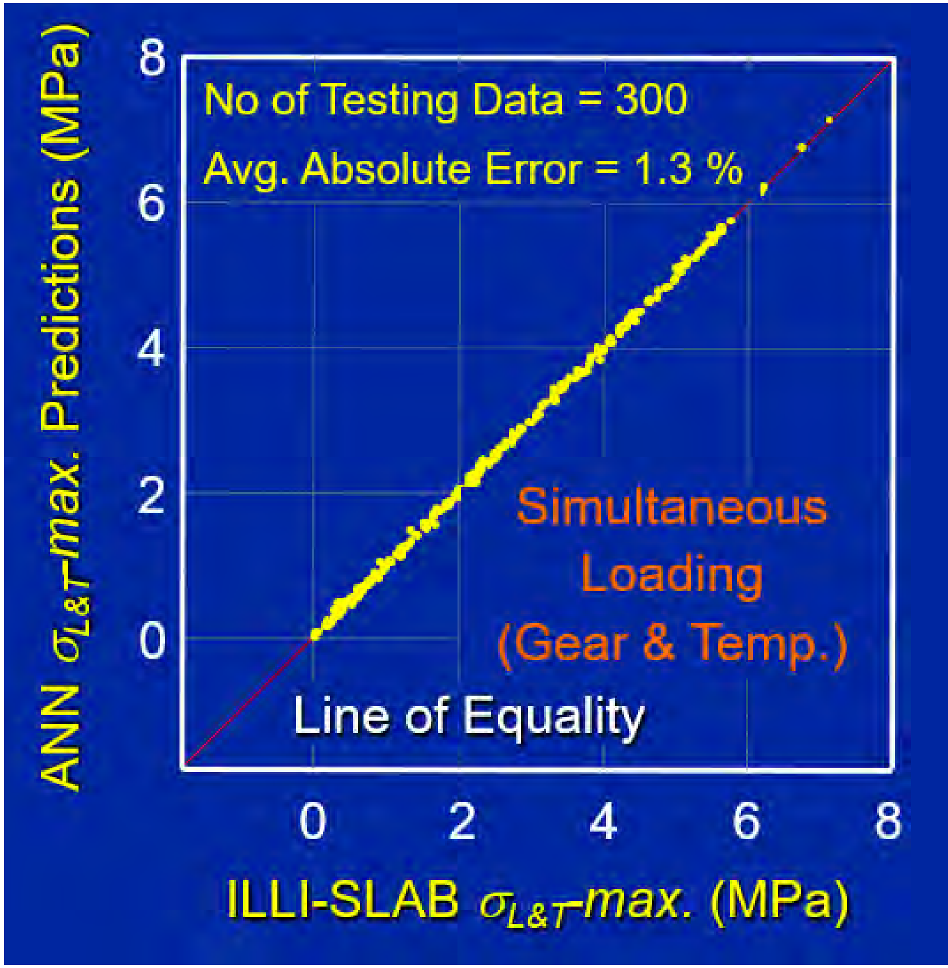
- ANN architecture examples





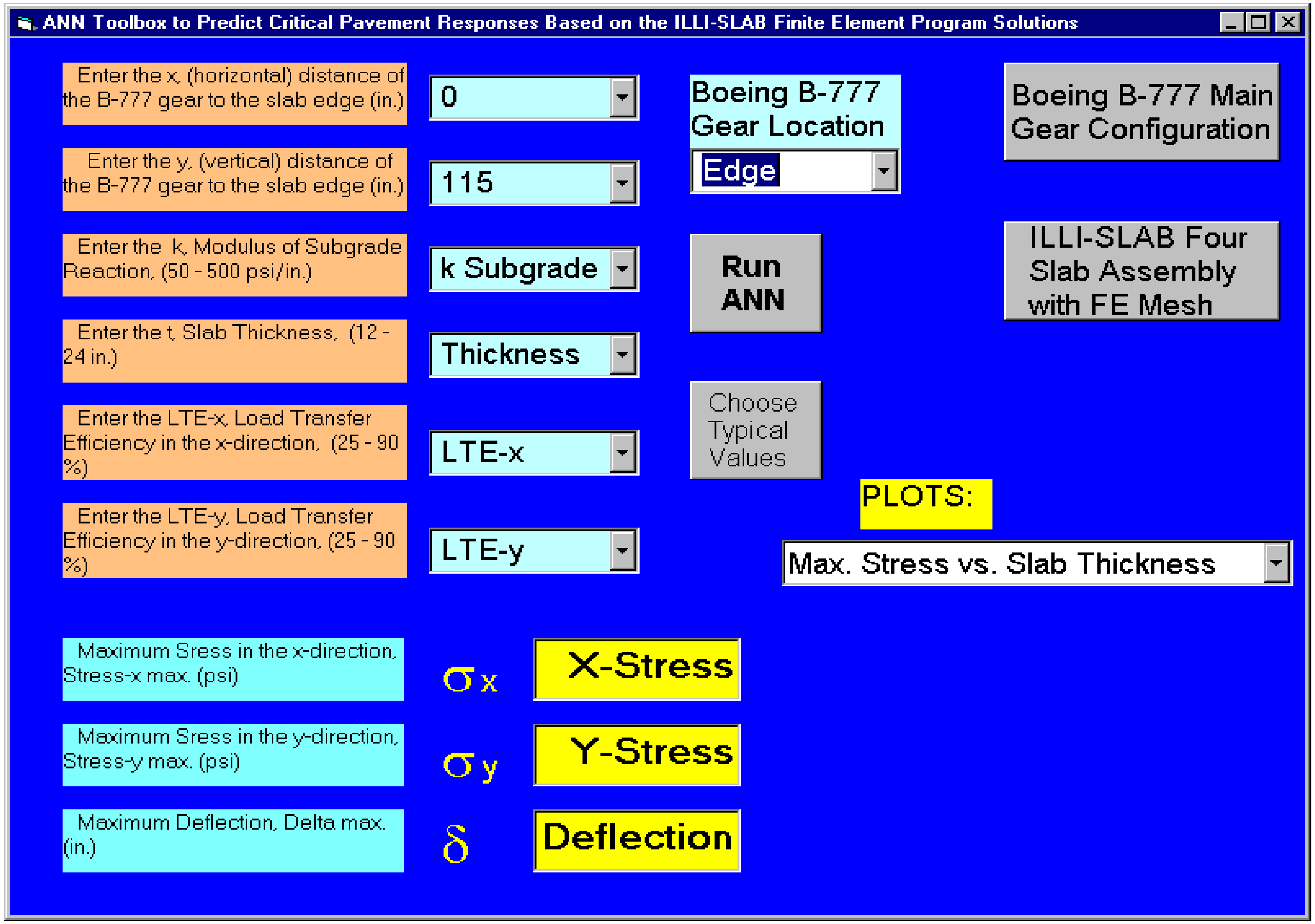
- ANN prediction examples





Analysis and Design of Concrete Pavement Systems Using ANN (Cont'd)

- ILLI-N Design Tool

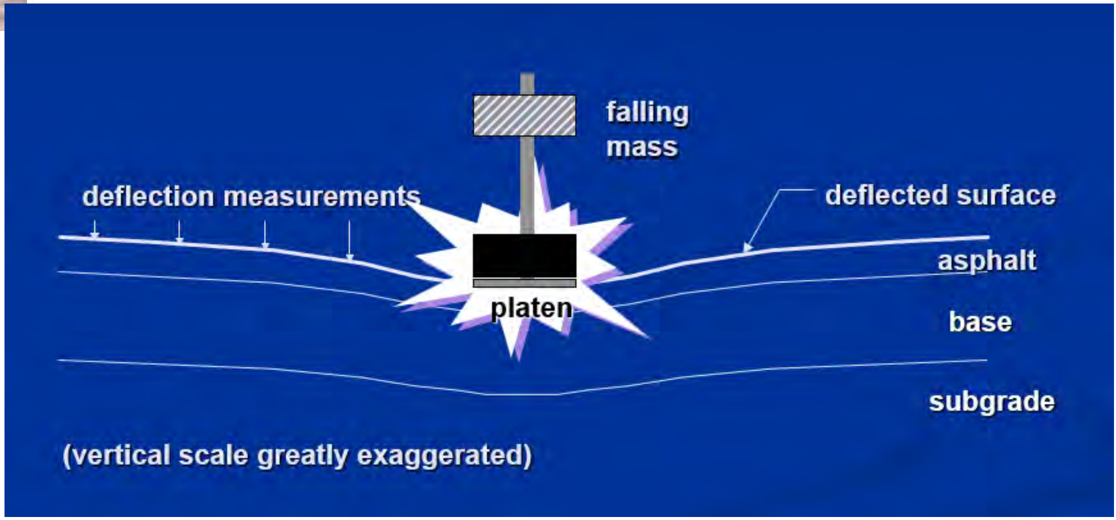


Nondestructive Structural Assessment of Concrete Pavements Using ANN

- Objectives
  - To develop ANN-based models for nondestructively assessing the condition of the concrete (rigid) pavement systems.
  - The backcalculated layer properties are:
    - Concrete pavement layer modulus (E_{pcc})
    - Coefficient of subgrade reaction (k_s)
    - Radius of relative stiffness (l)

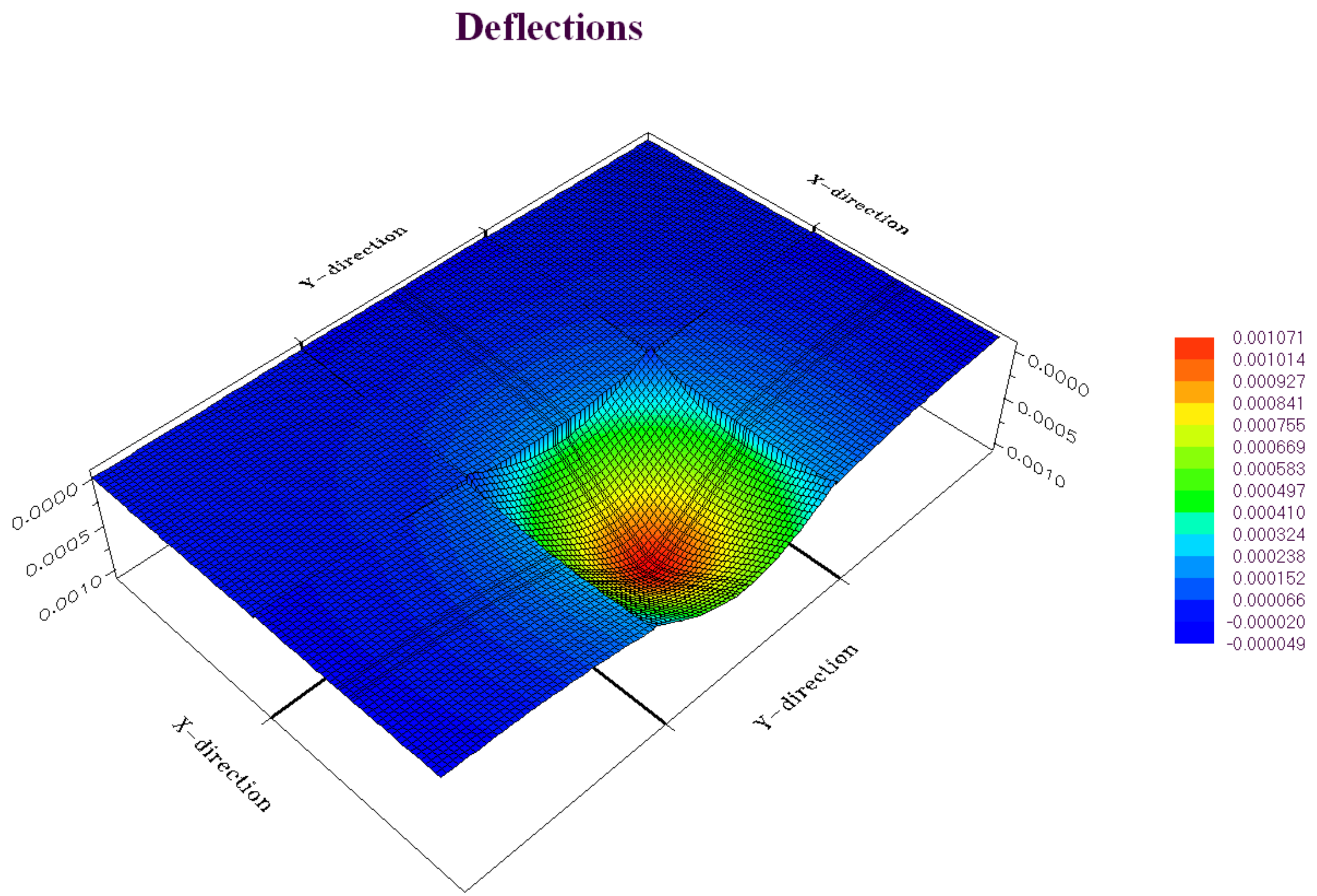
Nondestructive Structural Assessment of Concrete Pavements Using ANN (Cont'd)

- Falling Weight Deflectometer



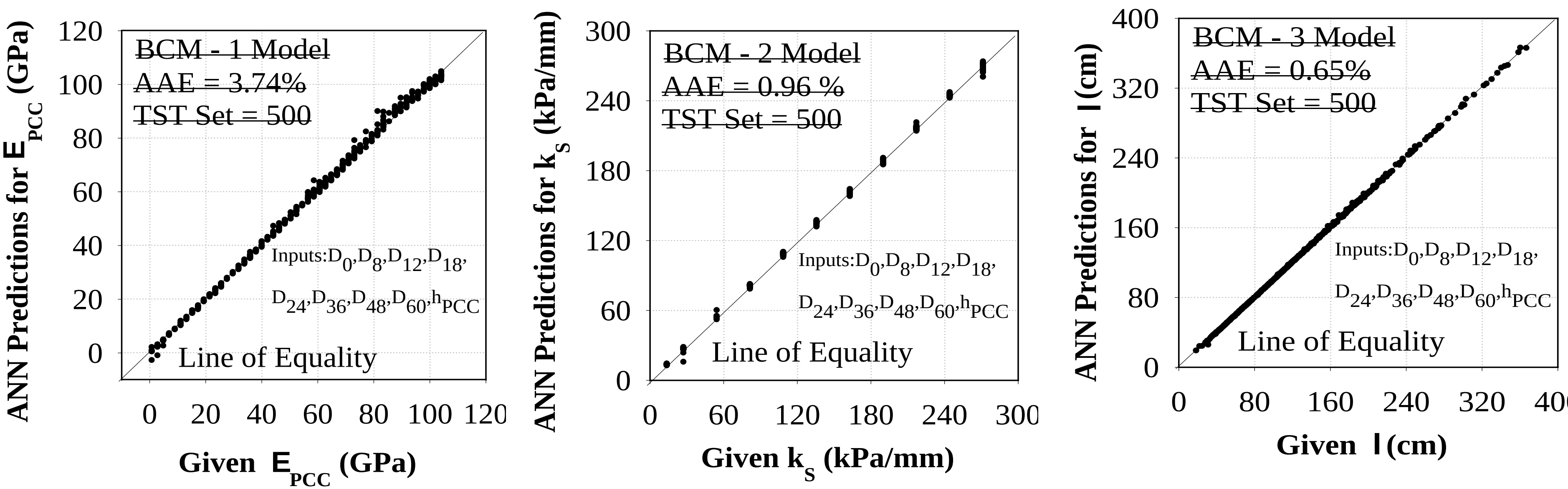
Nondestructive Structural Assessment of Concrete Pavements Using ANN (Cont'd)

- A deflection basin obtained from FE analysis



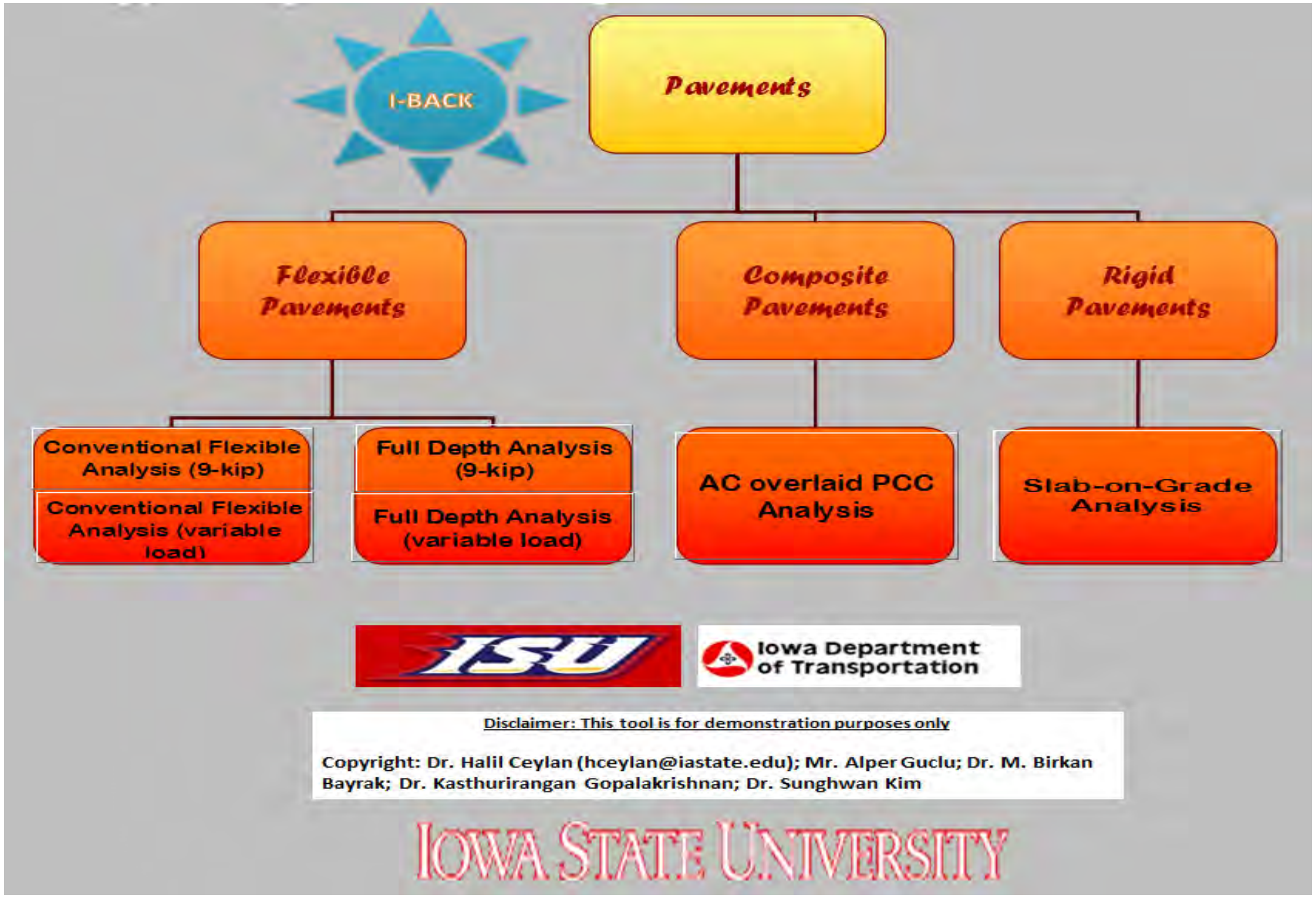
Nondestructive Structural Assessment of Concrete Pavements Using ANN (Cont'd)

- ANN-based backcalculation models



Nondestructive Structural Assessment of Concrete Pavements Using ANN (Cont'd)

- I-BACK: Iowa's Intelligent Pavement Backcalculation Software



Multiple-Slab Response Model for Top-Down Cracking Mode in Rigid Airport Pavements

- Existing FAA rigid pavement design

$$DF = \frac{R}{0.75 \times \boxed{\sigma_e}}$$

$$\frac{DF}{F_c} = \left[\frac{F'_s bd}{\left(1-\frac{SCI}{100}\right)(d-b)+F'_s b}\right] \times \log C + \left[\frac{\left(1-\frac{SCI}{100}\right)(ad-bc)+F'_s bc}{\left(1-\frac{SCI}{100}\right)(d-b)+F'_s b}\right]$$

$$\mathrm{CDF} = \frac{(\text{annual departures}) \times (\text{life in years})}{\left(\text{pass}/\text{coverage ratio}\right) \times (\text{coverages to failure})}$$

- •Design life (years)
- •Concrete flexural strength
- •Structural layer data (type and thickness)
- •Subgrade modulus (k or E)
- •Airplane traffic mix (type, weight, frequency)

Design Inputs

3D-FEM analysis

Calculate cumulative damage factor (CDF) for each aircraft

Total CDF=1

No

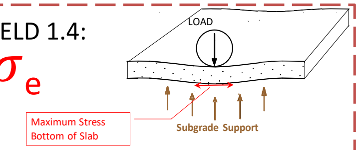
Iterates on the concrete layer thickness

Yes

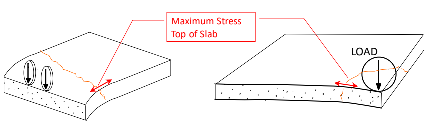
Concrete layer thickness

Satisfying the design conditions: **SCI=80**

FAARFIELD 1.4: σ_e

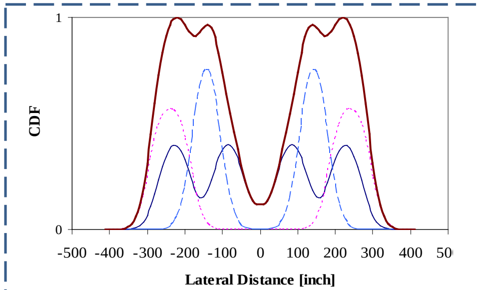


FAARFIELD 2.0:



3D-FEM:

- **Pros.**
- Provides the complete stress and displacement fields for the analyzed domain
- Handles complex load configurations easily
- Not limited to linear elastic analysis
- **Cons.**
- May require long computation times
- Pre-processing and post-processing requirements



Multiple-Slab Response Model for Top-Down Cracking Mode in Rigid Airport Pavements (Cont'd)

- Proposed FAA rigid pavement design

$$DF = \frac{R}{0.75 \times \boxed{\sigma_{critical}}}$$

$$\frac{DF}{F_c} = \left[\frac{F_s' bd}{\left(1-\frac{SCI}{100}\right)(d-b)+F_s' b}\right] \times \log C + \left[\frac{\left(1-\frac{SCI}{100}\right)(ad-bc)+F_s' bc}{\left(1-\frac{SCI}{100}\right)(d-b)+F_s' b}\right]$$

$$\mathrm{CDF} = \frac{(\text{annual departures}) \times (\text{life in years})}{\left(\text{pass}/\text{coverage ratio}\right) \times (\text{coverages to failure})}$$

- Design life (years)
- Concrete flexural strength
- Structural layer data (type and thickness)
- Subgrade modulus (k or E)
- Airplane traffic mix (type, weight, frequency)

Design Inputs

Surrogate critical response model

Calculate CDF (for each aircraft)

Total CDF=1

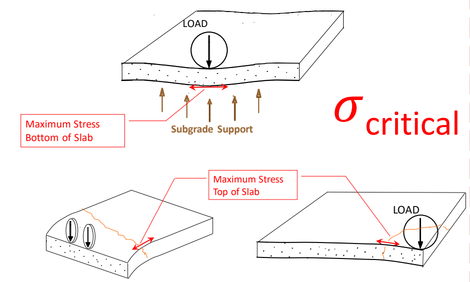
No

Iterates on the concrete layer thickness

Yes

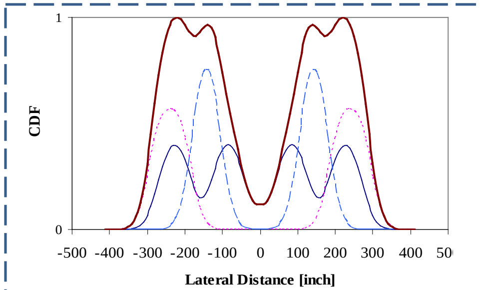
Concrete layer thickness

Satisfying the design conditions: **SCI=80**



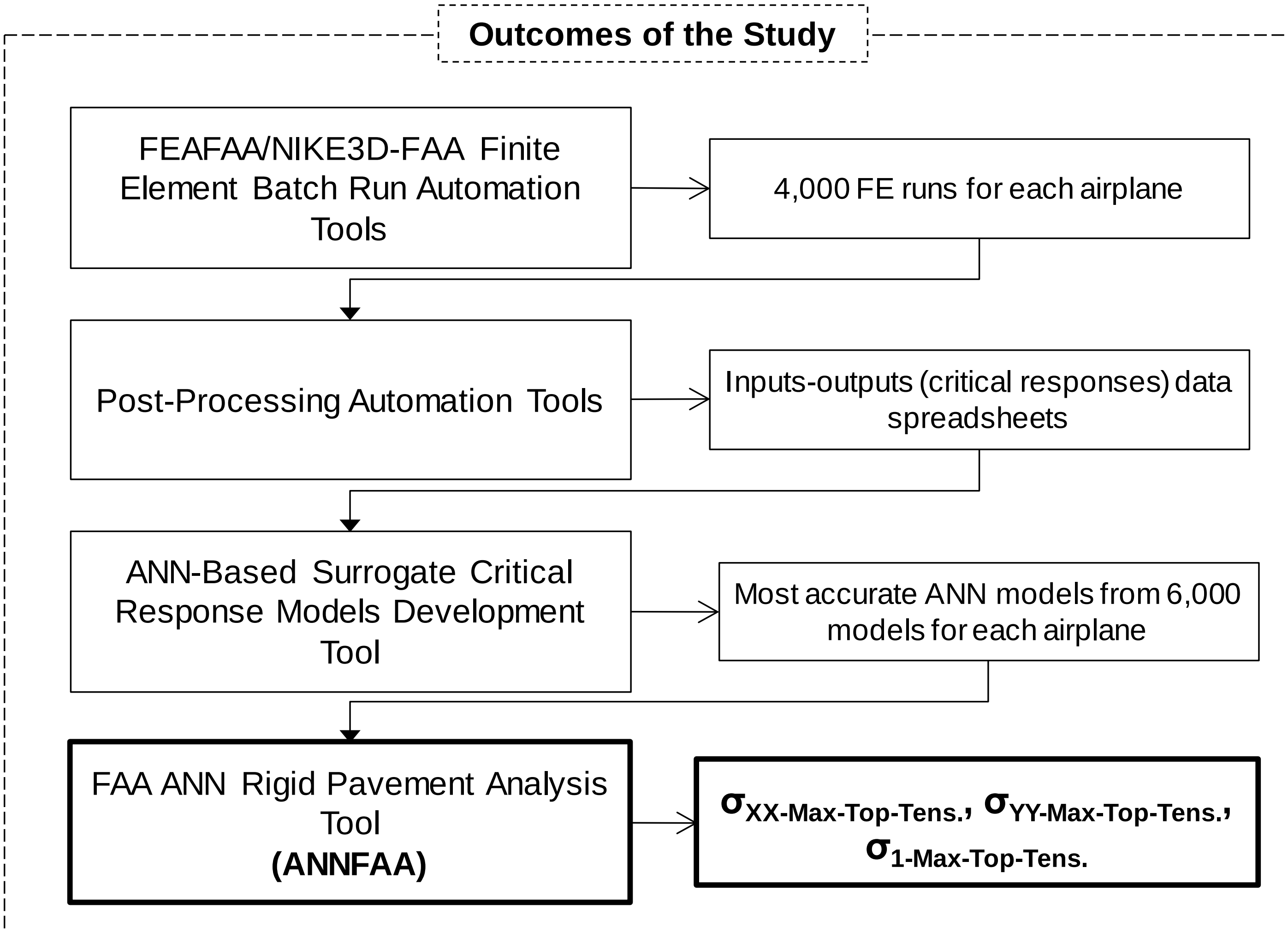
$\sigma_{critical}$

- Return a close estimate of critical responses computed by FEM analysis for combined vehicle and temperature loading in rigid airport pavement
- Enable faster 3D-FE computations of design stresses in FAARFIELD 2.0 making it suitable for routine design
- Pavement foundation response and moduli prediction models
- Enable using 9-slab pavement structure without increasing computational time

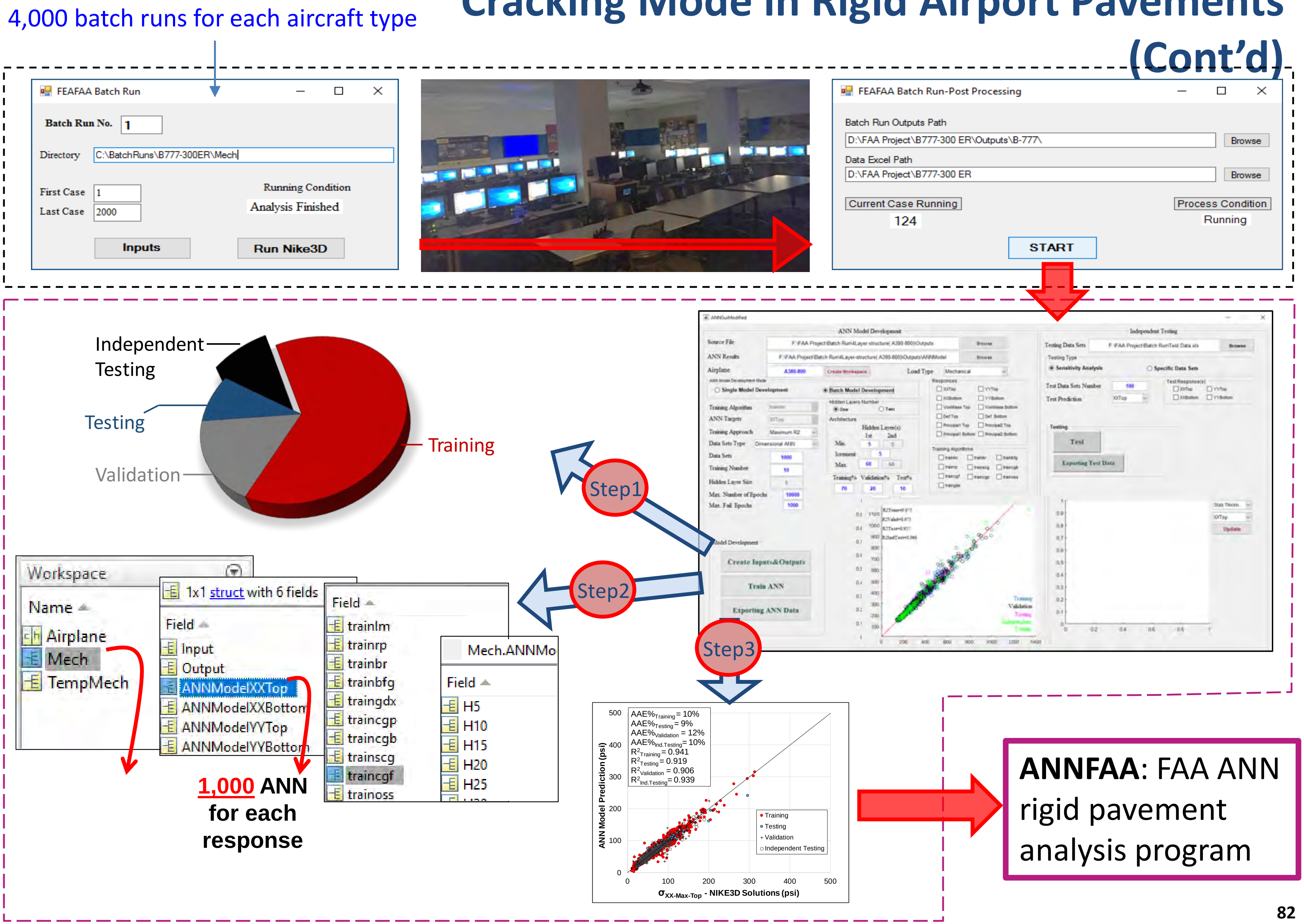


Multiple-Slab Response Model for Top-Down Cracking Mode in Rigid Airport Pavements (Cont'd)

- Methodology

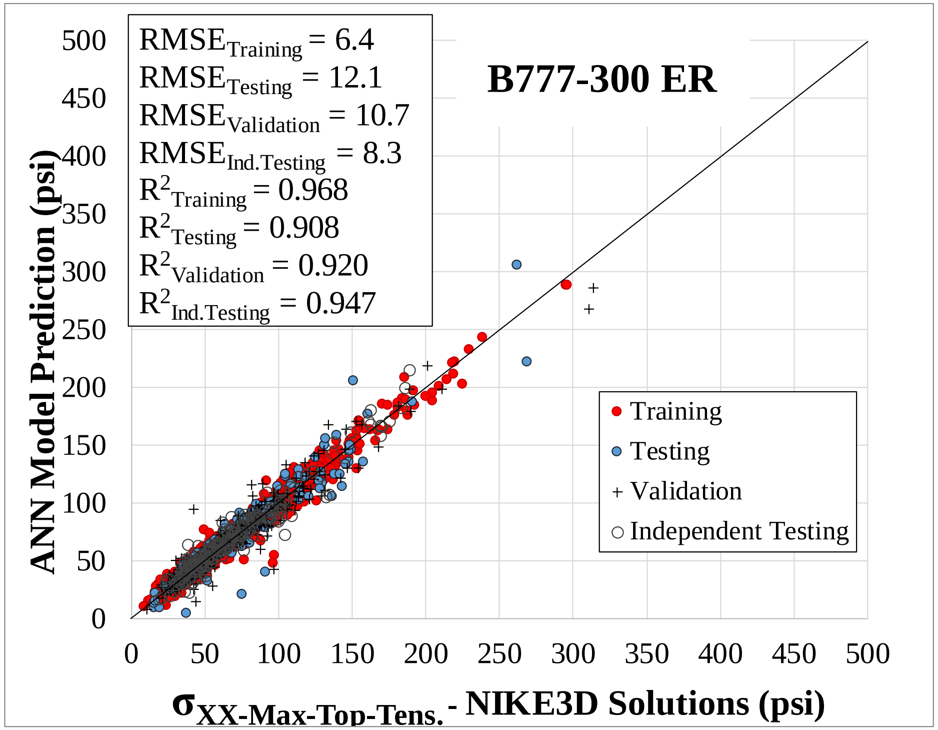


Multiple-Slab Response Model for Top-Down Cracking Mode in Rigid Airport Pavements (Cont'd)

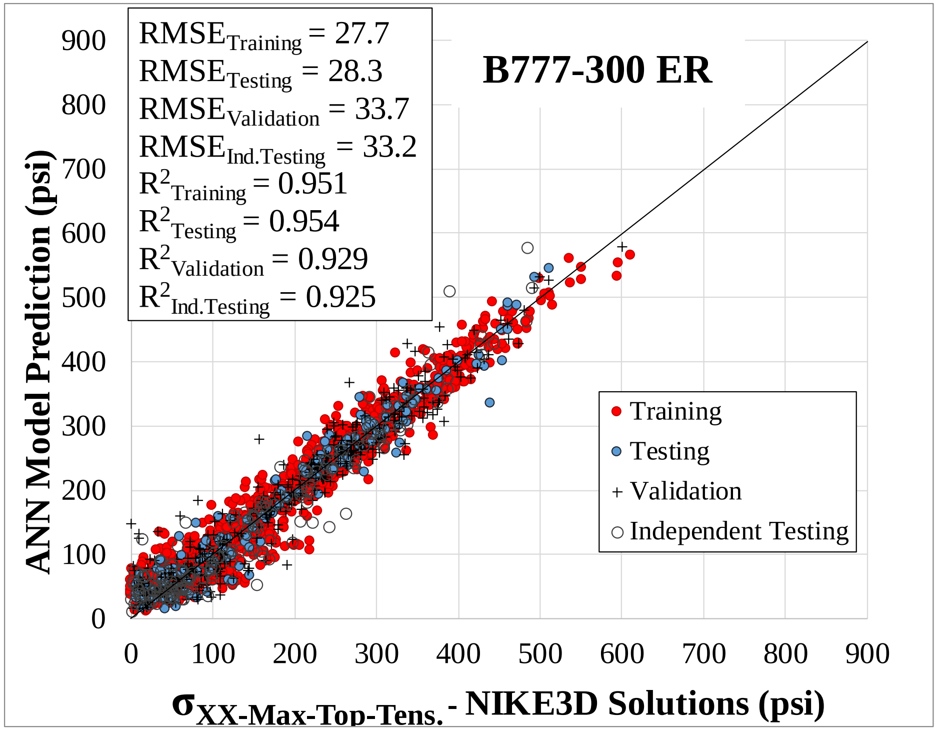


Multiple-Slab Response Model for Top-Down Cracking Mode in Rigid Airport Pavements (Cont'd)

- ANN model performance accuracy



Mechanical Loading

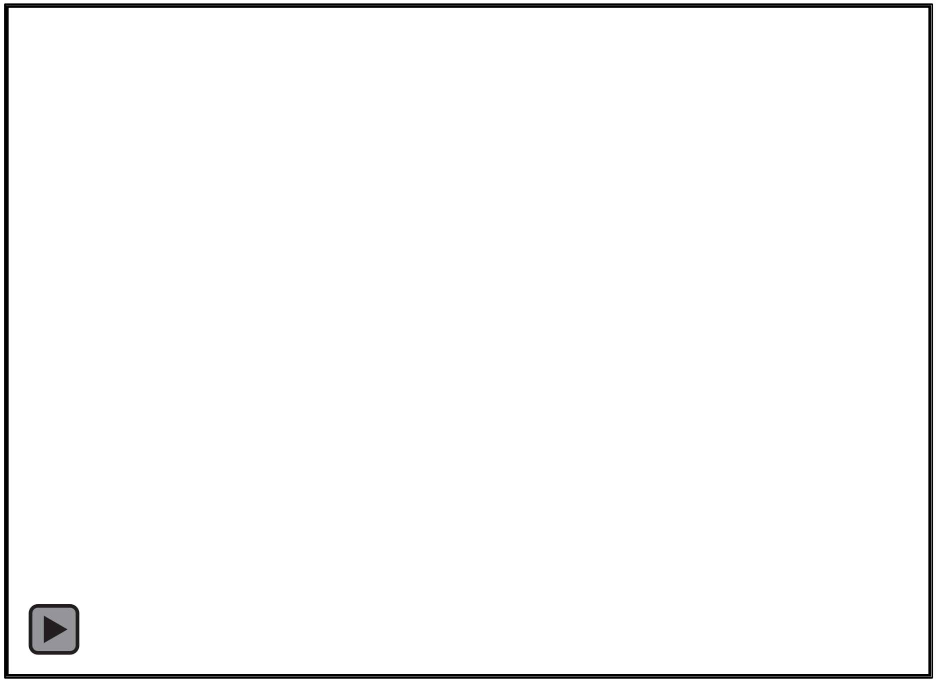


Mechanical + Temperature Loading

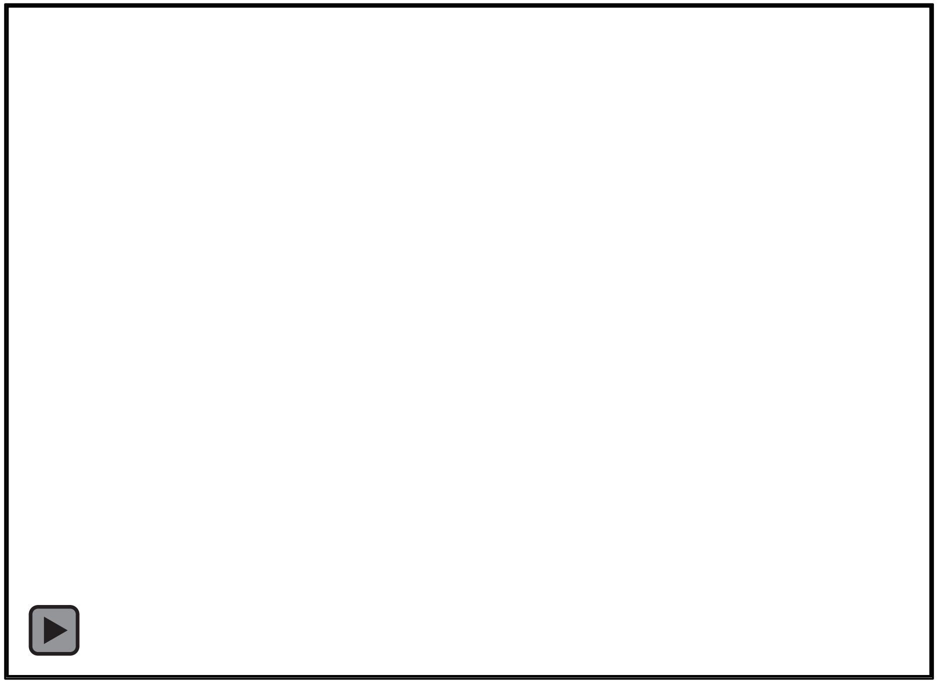
Multiple-Slab Response Model for Top-Down Cracking Mode in Rigid Airport Pavements (Cont'd)

- ANNFAA: FAA ANN rigid pavement analysis tool
  - ANNFAA vs. FEAFAA

ANNFAA



FEAFAA

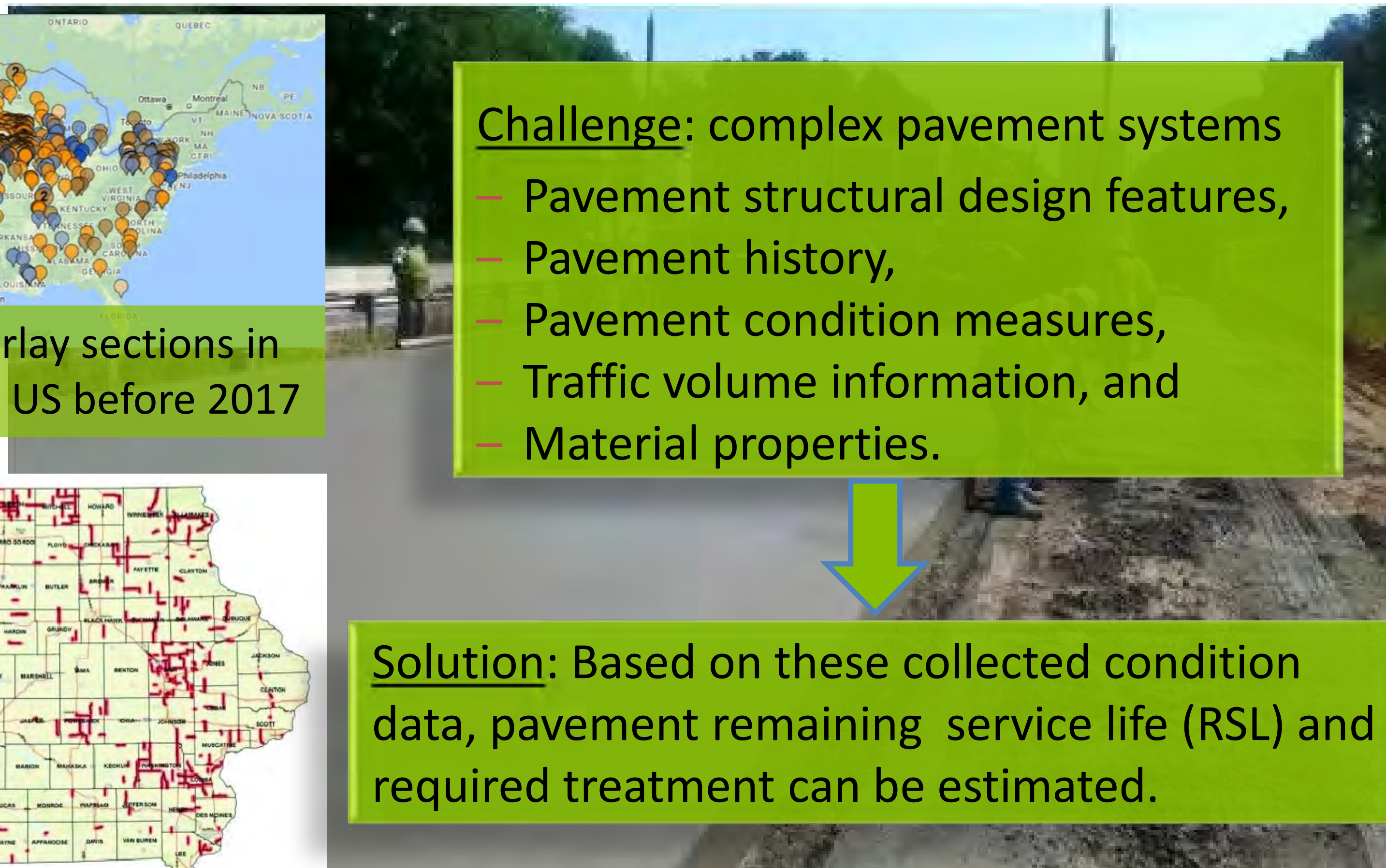


AI for Predicting PCC Overlay Performance

<u>Portland cement concrete (PCC) Overlays</u>[1,2]

1,289 PCC overlay sections in 46 states in the US before 2017

About 40% -- in Iowa!

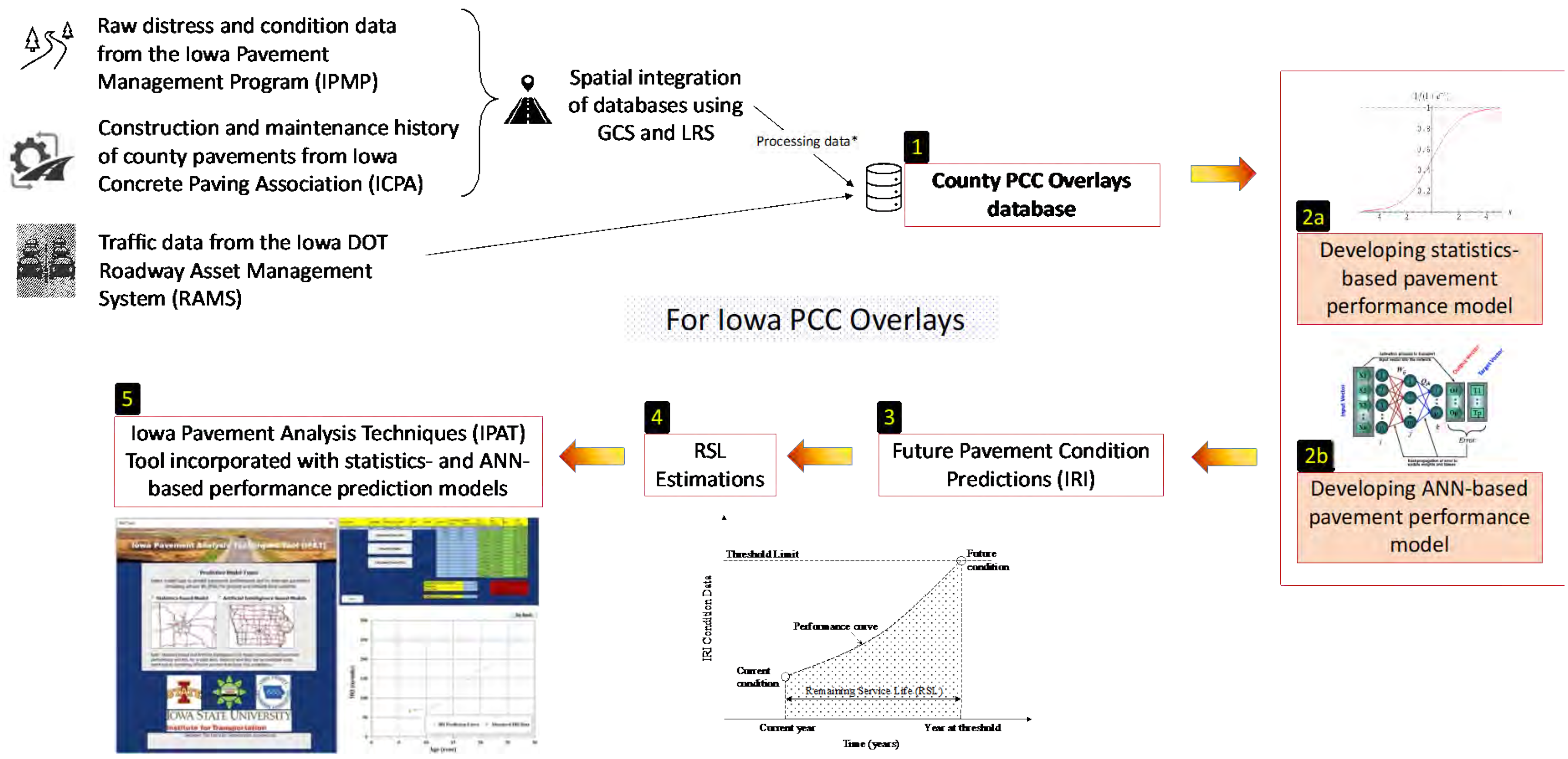


<u>Challenge</u>: complex pavement systems

- Pavement structural design features,
- Pavement history,
- Pavement condition measures,
- Traffic volume information, and
- Material properties.

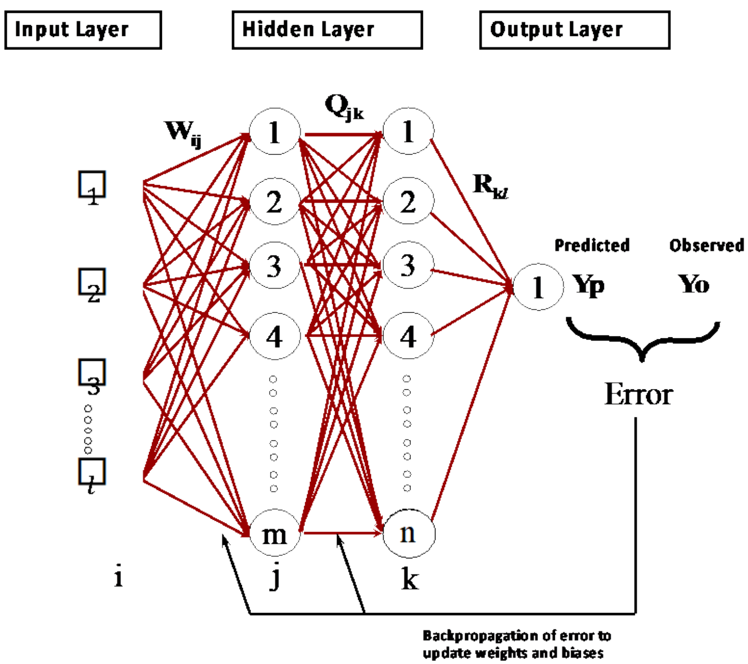
<u>Solution</u>: Based on these collected condition data, pavement remaining service life (RSL) and required treatment can be estimated.

AI for Predicting PCC Overlay Performance (Cont’d)



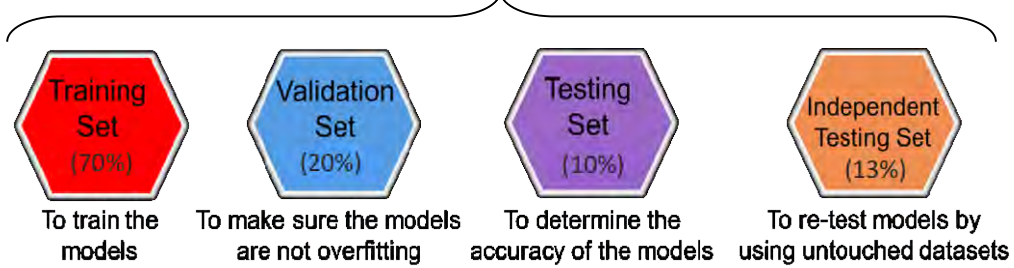
AI for Predicting PCC Overlay Performance (Cont'd)

- The prediction model was trained using Levenberg-Marquardt ANN algorithms with a hyperbolic tangent activation function



Schematic of a typical ANN architecture

148 road sections (1,284 data points)



AI for Predicting PCC Overlay Performance (Cont'd)

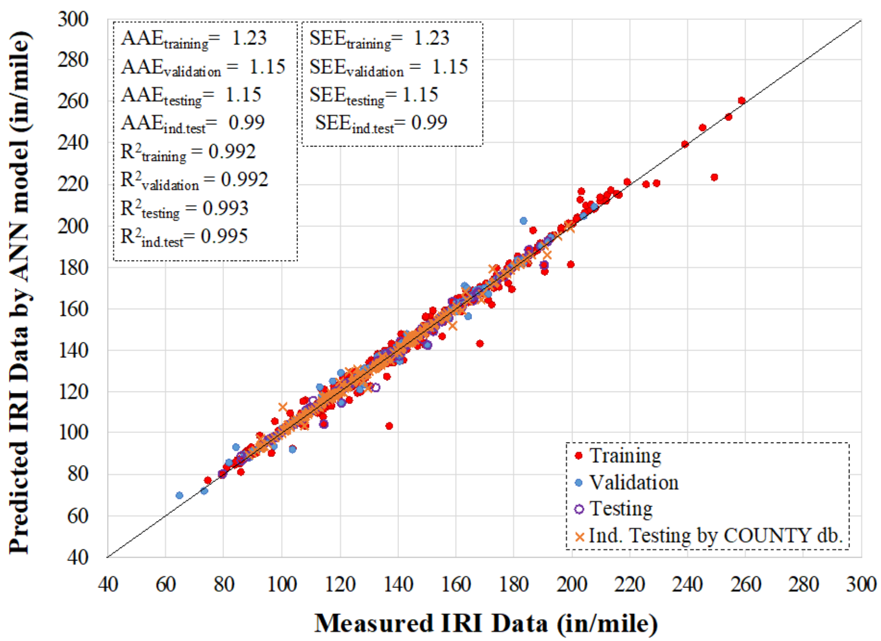
Input and output parameters used in ANN Model development – IRI pred.

Model Name	Input Parameters	Output Parameter
IRI ANN Model	Age Overlay thickness (in.) Traffic (accumulated AADTs) Joint spacing (ft.) IRI $_{(i-2)\ year}$ (in/mile) IRI $_{(i-1)\ year}$ (in/mile)	IRI $_{(i)\ year}$ (in/mile)

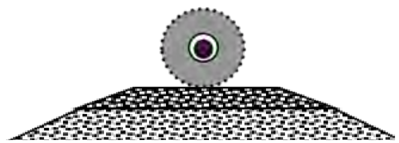
Input ranges used in developing and testing ANN models

ANN-based IRI model	Input ranges used for training ANN model		Input ranges used for indp. testing ANN model	
	Min	Max	Min	Max
Overlay thickness (in.)	2	10	5	8
Traffic (accumulated AADT)	120	90,600	240	38,750
Pavement age (yr.)	4	52	4	38
Joint spacing (ft.)	0	40	6	20
IRI $_{(i-2)\ year}$ (in./mile)	60.5	249.7	82.4	190.9
IRI $_{(i-1)\ year}$ (in./mile)	62.8	254.5	87.5	195.3

- 6-15-1 ANN Model Results



- Overview: pavement deterioration and remaining service life (RSL/RSI) model development stages

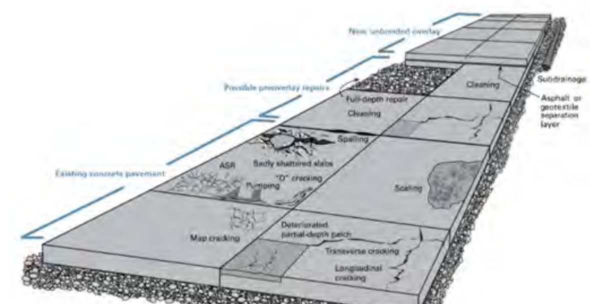


- Pavement Structure
- Traffic
- Age

Pavement Performance Models are Developed

Project-Level

Network-Level



Pavement Condition (Distresses/Smoothness)

Estimated RSL

Using Developed Pavement Performance Models

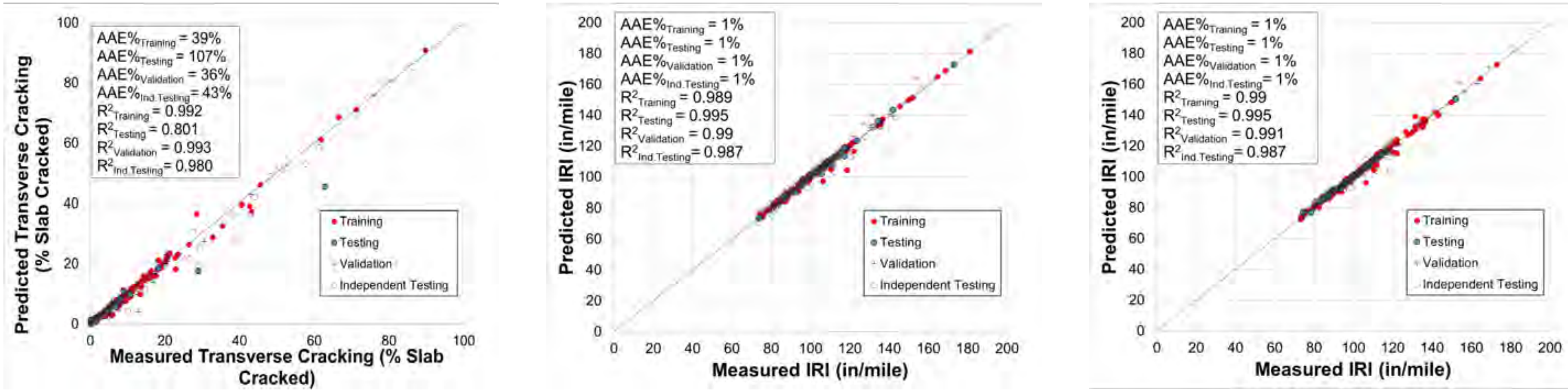
Using RSL Models and Corresponding FHWA-defined Threshold Limits for Performance Indicators

Future Pavement Condition Predictions (Distresses/Smoothness)

Development of IPAT (Cont’d)

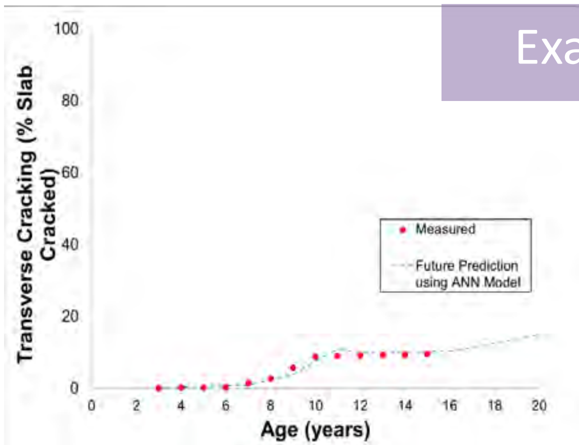
- A set of AI models were developed for each distress type as well as IRI predictions for various Iowa pavement types, including JPCP and PCC overlay
- Microsoft Excel Macro based network-level pavement deterioration prediction automation tool was developed that predicts future pavement performance using optimized AI models

Development of IPAT (Cont'd)

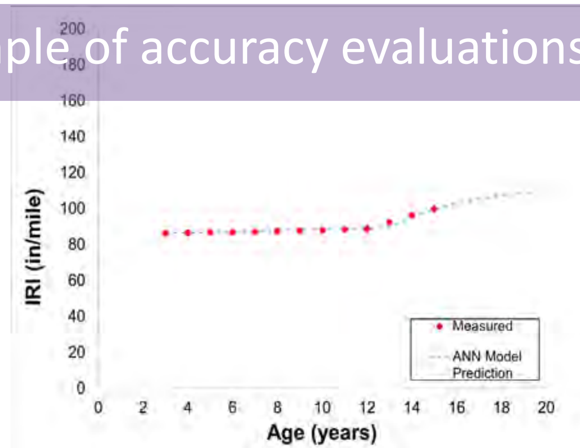


Comparisons between measured pavement condition records and ANN model predictions for JPCP pavements

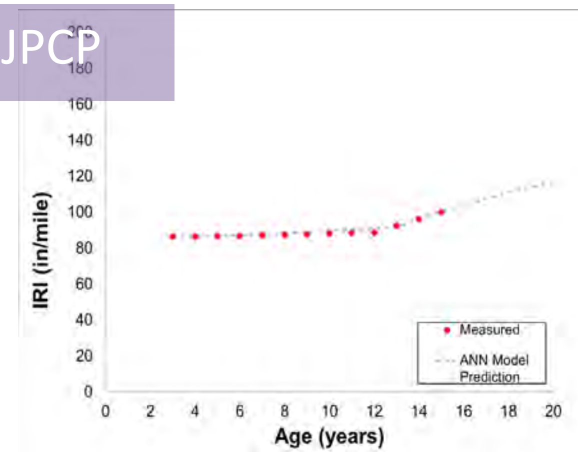
Example of accuracy evaluations : JPCP



Transverse cracking



IRI (approach 1)

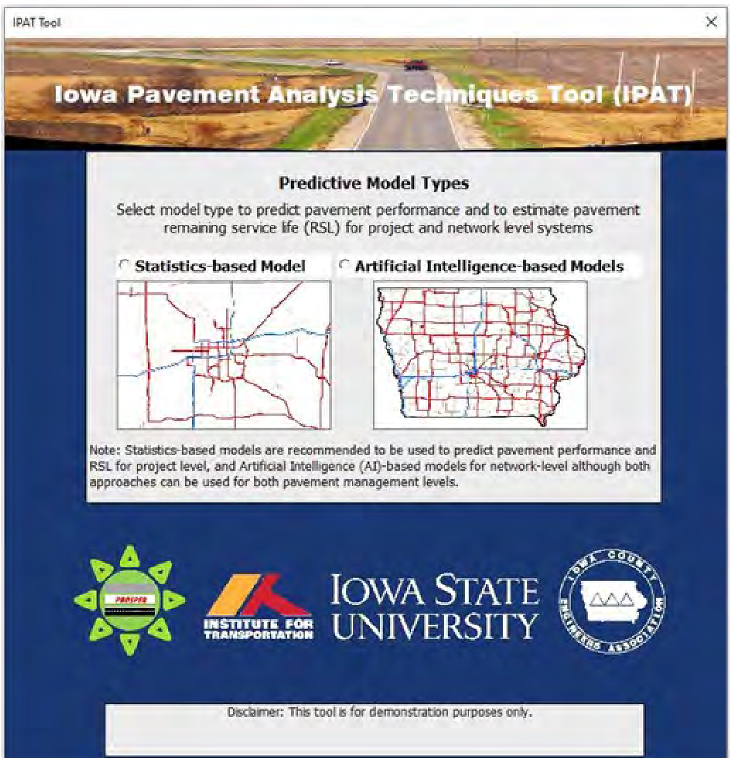


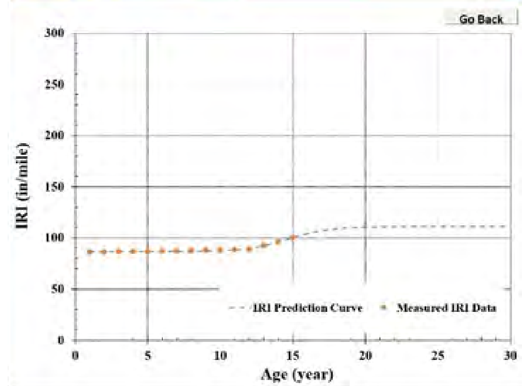
IRI (approach 2)

Comparisons between measured pavement condition records and ANN model predictions for a JPCP pavement section as an example (IA 5, MP 85.24 to 88.06, N, Traffic (AADTT): 799, Construction year: 1999)

Development of IPAT (Cont’d)

- IPAT tool interface including navigation panel (left), sub-tool for pavement performance prediction (top right), and performance predictions over time (bottom right)



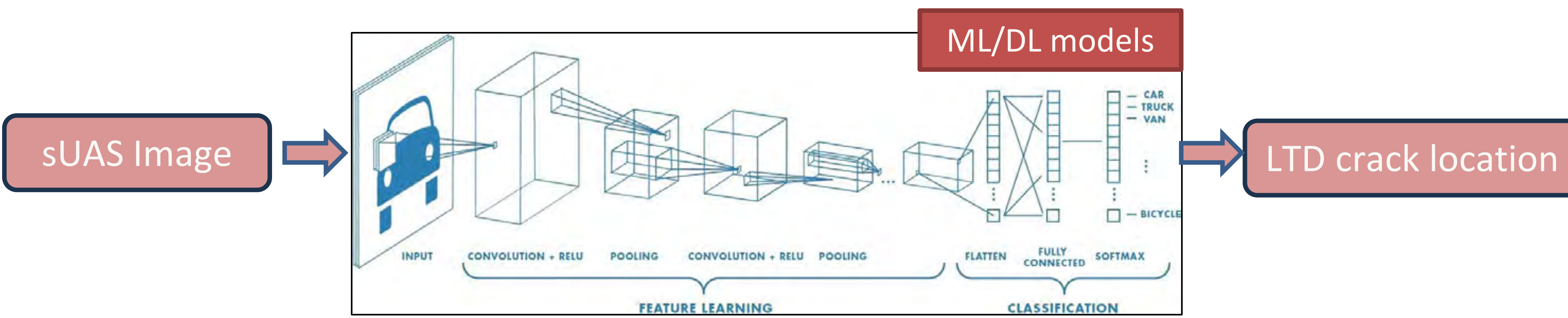


Use of sUAS and ML/DL for Airport Pavement Inspection and Rating

- Motivation
  - Routine airfield pavement inspections are crucial for maintaining safe and serviceable airfield pavement
  - Current practice for airport inspections relies on visual surveys and manual interpretation
  - sUAS has attracted attention as cost-effective and efficient pavement inspection tools

Use of sUAS and ML/DL for Airport Pavement Inspection and Rating (Cont'd)

- Methodology
  - ML and DL models been widely used for object detection
  - There is a scope of applying ML and DL on drone data for pavement distress such longitudinal, transverse, and diagonal cracks detection and assist traditional pavement inspection



Use of sUAS and ML/DL for Airport Pavement Inspection and Rating (Cont'd)

- Data collection using sUAS

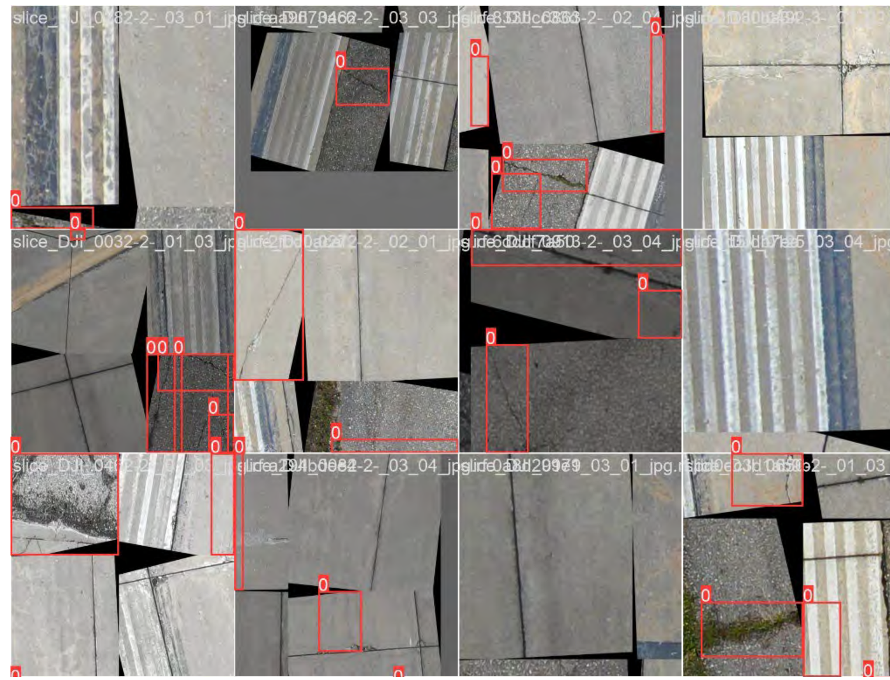
Use of sUAS and ML/DL for Airport Pavement Inspection and Rating (Cont'd)

- ML and DL model development

sUAS collected color image → Image split into 4m x 3 m size → Data cleaning → Annotation → Data augmentation → Train, Test, & Validation dataset

Use of sUAS and ML/DL for Airport Pavement Inspection and Rating (Cont'd)

- Results



Use of AI for Predicting Concrete Compressive Strength

- Objectives
  - Concrete compressive strength is a highly nonlinear function of age and ingredients
  - Ingredients include - cement, blast furnace slag, fly ash, water, superplasticizer, coarse aggregate, and fine aggregate
  - Use AI models to predict concrete compressive using ingredients and age

Use of AI for Predicting Concrete Compressive Strength (Cont’d)

- AI models utilized
  - Linear regression
  - Decision Tree Regression
  - Random Forrest Regression
  - ANN with Levenberg–Marquardt algorithm
  - Data contained
    - Inputs: *Cement Amount, Blast Furnace Slag, Fly Ash, Water, Superplasticizer, Coarse Aggregate, Fine Aggregate, and Age*
    - Output: *Compressive Strength*

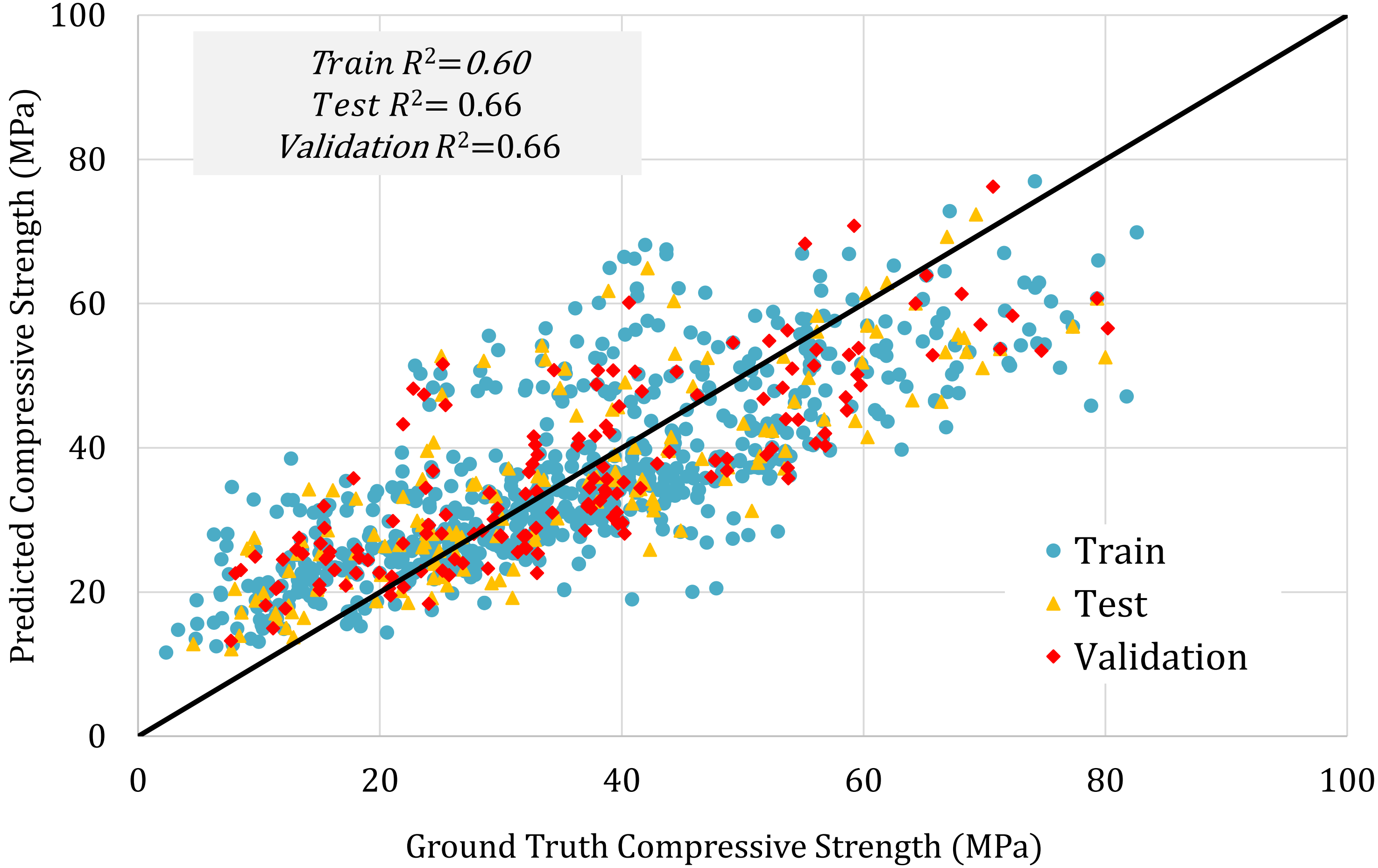
Use of AI for Predicting Concrete Compressive Strength (Cont’d)

- Results summary

Model + Properties	Train R^2	Test R^2	Validation R^2
Linear regression	0.60	0.66	0.66
Decision Tree Regression	0.91	0.84	0.79
Random Forrest Regression	0.98	0.90	0.89
ANN models developed with using Levenberg–Marquardt algorithm (MLPs)	**0.99**	**0.96**	**0.98**

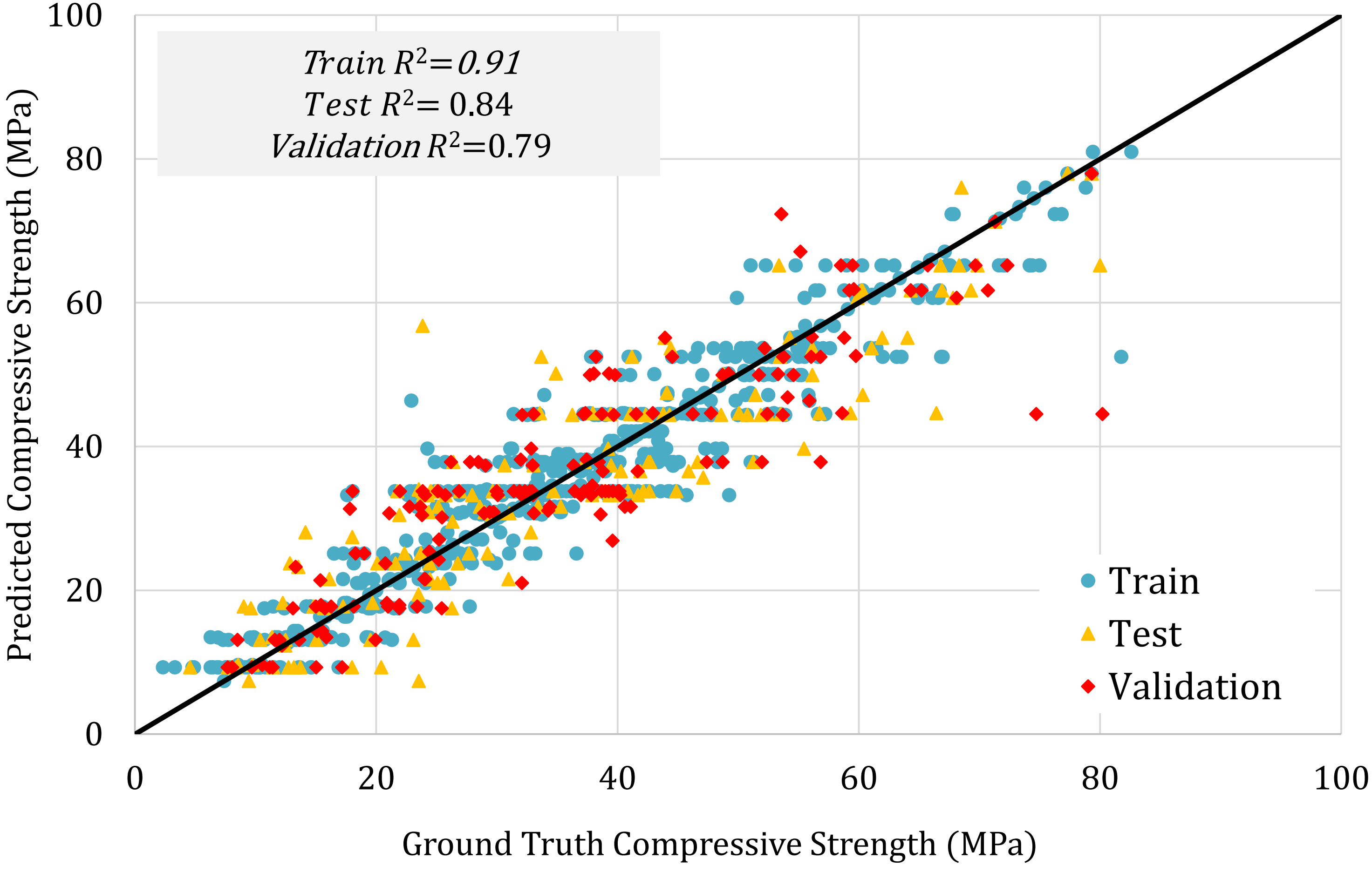
Use of AI for Predicting Concrete Compressive Strength (Cont'd)

- Results: Linear Regression Model



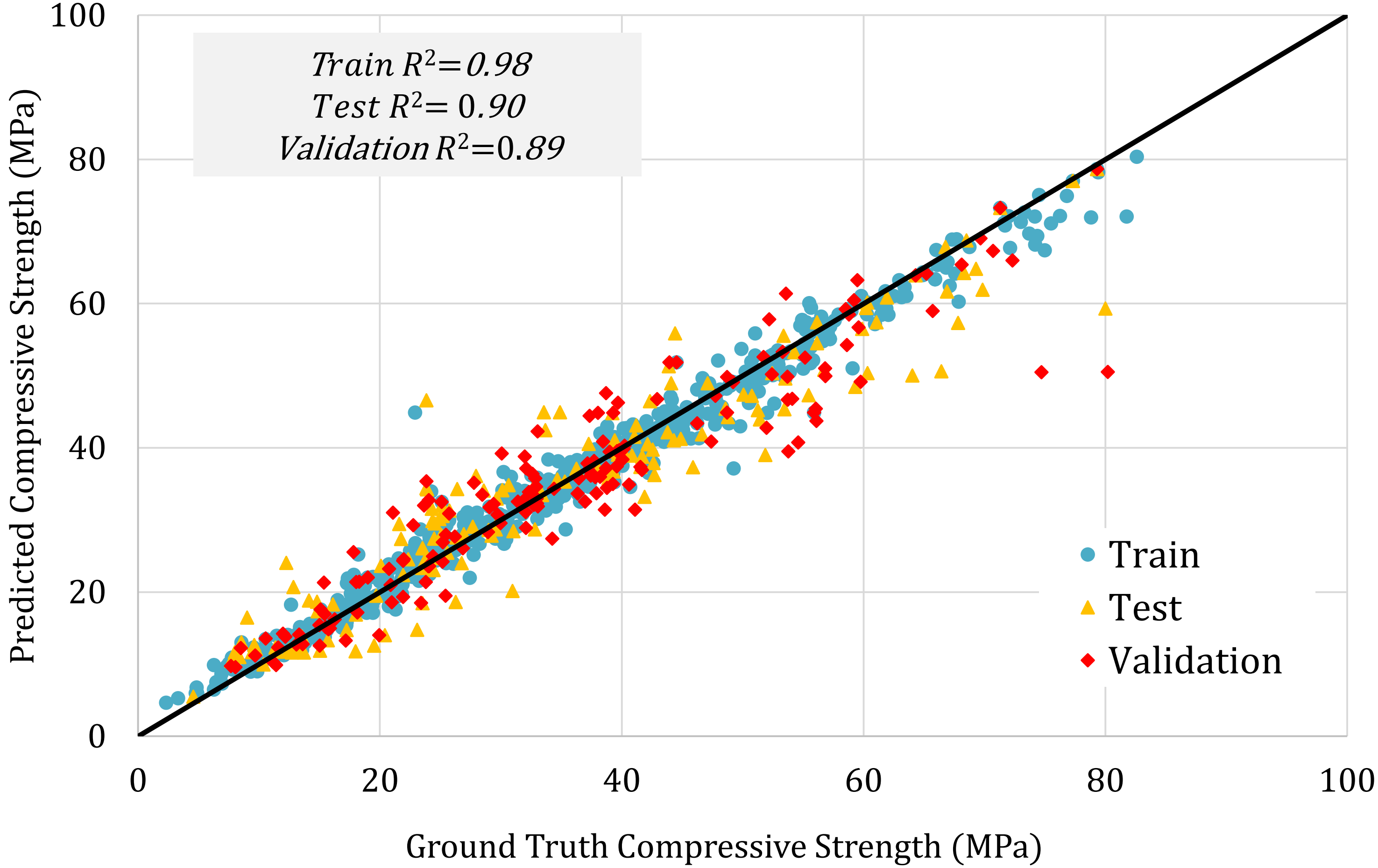
Use of AI for Predicting Concrete Compressive Strength (Cont'd)

- Results: Decision Tree (max-depth 7)



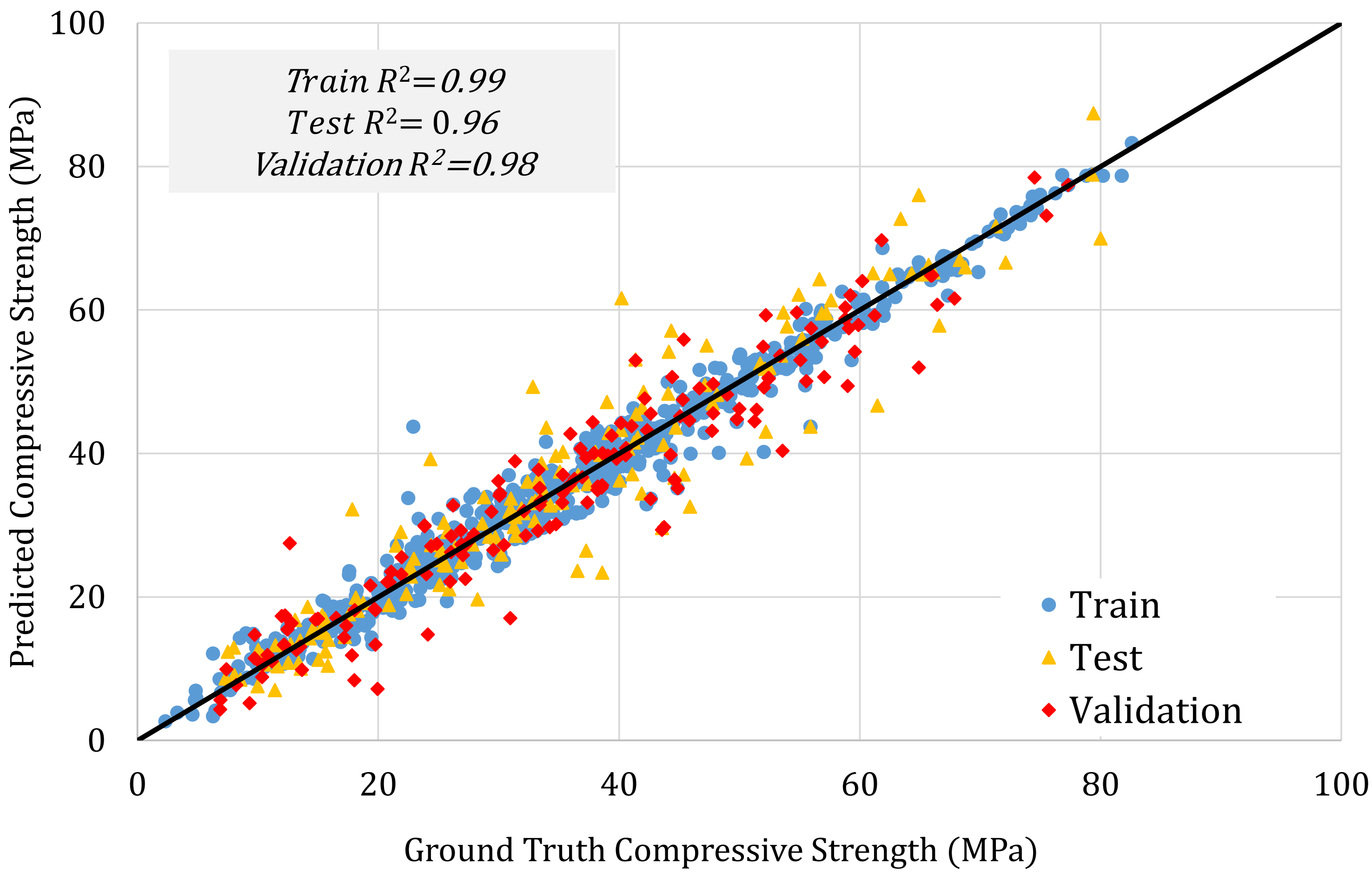
Use of AI for Predicting Concrete Compressive Strength (Cont'd)

- Results: Random Forest (20-trees)



Use of AI for Predicting Concrete Compressive Strength (Cont'd)

- Results: ANN with Levenberg–Marquardt Algorithm



Outline

- Introduction: Fundamentals of Concrete and Artificial Intelligence (AI)
- Advent of AI in Concrete Science and Technology
- Applications of AI in Concrete Design and Construction
- Case Studies and Success Stories: Dr. Ceylan's Research on use of AI for Concrete Pavement Systems
- Summary

Summary: Overall

- AI shows promise for use for investigating, modelling, and generally achieving better understanding of complex and non-linear engineering problems and mechanisms, even for some that have not yet been well understood or formulated

- The high potential of AI techniques in solving resource-intensive complex problems has led to increased interest in using these methods in various engineering areas

Summary: Overall (Cont'd)

- Over recent decades, use of AI technique has been popular both in research and industrial applications
- AI has been used in a wide variety of concrete science and technology associated with design, construction, and asset management applications

Summary: Benefits and Advantages

- Prediction of target properties
- Increase accuracy
- Improvement and acceleration of computational simulations
- Automation
- Risk mitigation

Summary: Challenges

- Data challenge
  - Data sparsity
  - High dimensionality
  - Data bias
- Validation challenge
  - Hold-out method
  - Cross-validation
- Interpretability challenge
  - Diagnostics
  - Causality
- Sharing data and tools
- Linking laboratory and field data

Summary: Direction for Practitioners to Use AI

- Starting with simple models
  - Simpler models with fewer coefficients or assumptions are preferable to complex one
  - Prediction accuracy and the data accuracy
  - Complex models with less interpretability may only be utilized when additional accuracy gain is significant and necessary
- Knowing when to trust a model
  - Consensus on when to trust the models needs to be reached
  - Reported performance measures (e.g., accuracy) of AI models should be interpreted with caution
  - Inability to understand how the algorithms work is a central concern
- Physics-guided
  - Physical laws describing micromechanical responses, degradation mechanisms, and chemical reactivity should be utilized for data preprocessing

Summary: Industry Adaptation and Integration of AI

- Welcome change for adapting new technologies to stay ahead
- Identify strategy pining down the key use cases
- Implement the AI projects
- Get ready to accelerate
- See the bigger picture


Thank You

Questions?


Contact Information

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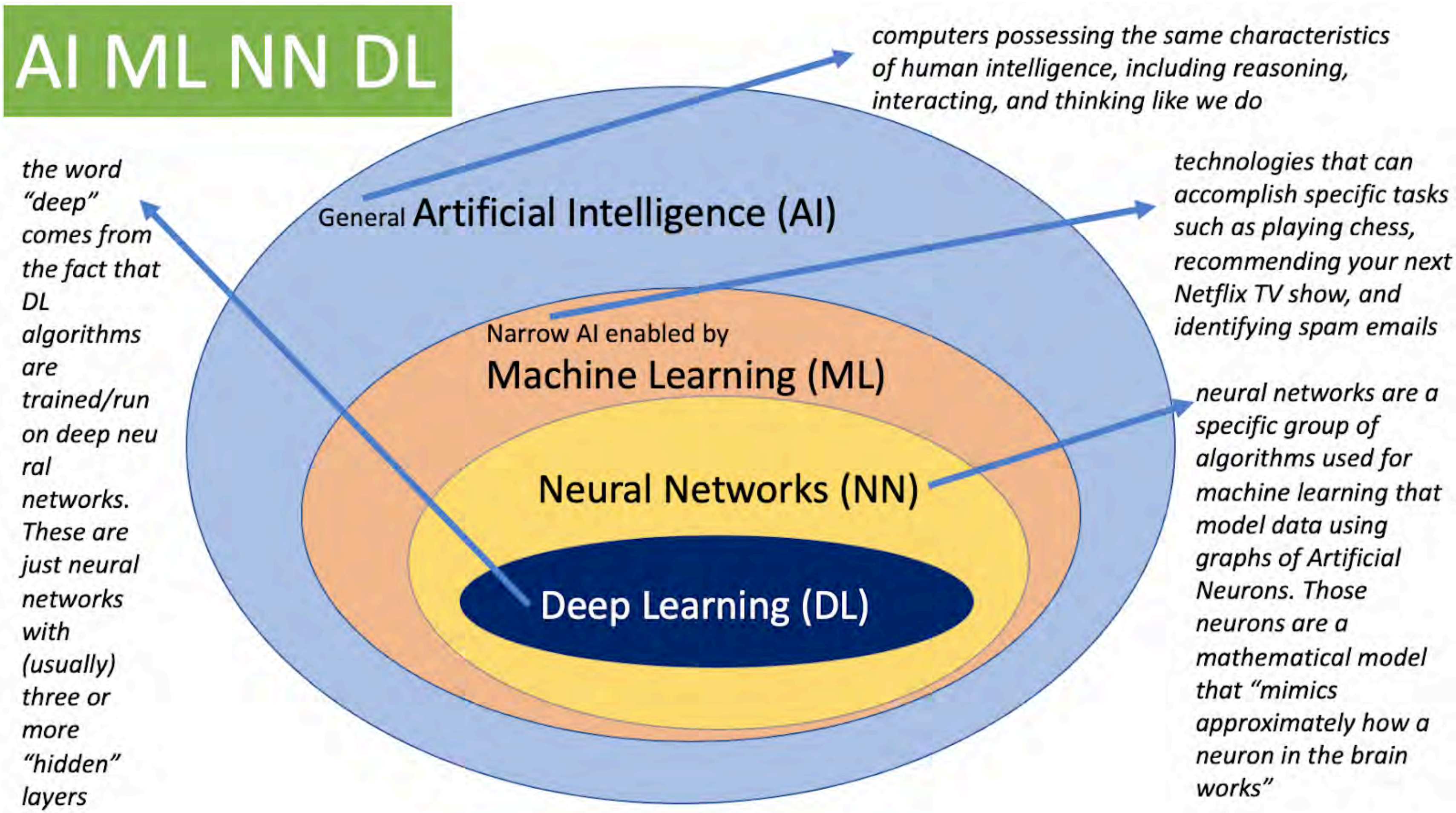
EXTRA SLIDES

AI: Types



(Image Source: https://www.greatillustrations.top/ProductDetail.aspx?iid=155812016&pr=42.88)

Applications of AI and ML in Concrete Mix Design (Cont'd)

- ML can be used to optimize certain proportions of specific materials in the mix
  - For example, Nunez et al. (2020) used hybrid ML to optimize the mix design for recycled aggregate concrete to use more recycled concrete

- In different attempts, Zhang et al. (2020) used ML and metaheuristic algorithms to optimize the mix proportions of concrete
  - Based on the multiple objectives to be achieved the slump, cost, and strength
  - That helped to predict these parameters even before the construction of the project based on historical data

Applications of AI and ML in Fresh Concrete Properties Prediction

Concrete parameter	Method	Tool for data acquisition	Reliability	Application	References
Slump and strength	Backpropagation neural networks	Actual data from RMC plant with 93 records	Slump prediction accuracy is less than for strength prediction	Slump for ready mix concrete	Dias and Pooliyadda (2001)
Concrete Temperature	ML of classification and regression tree	Radio-frequency identification (RFID)	98%	To prevent concrete surface cracks, manage the curing of the concrete and adopt preventative measures.	Xie et al. (2020)
Slump flow	Support Vector Regression, M5P Trees, Random Forest, and MLPReg	Lab experiments with 103 datasets	MLPReg predicted optimum	Predict slump flow for HPC	Unlu (2020)
Slump flow, t50 and J-ring	Extreme learning machine and long short-term memory (LSTM)	48 mixtures in the laboratory	The slump flow, t50, and J-ring with 99.71%, 81%, and 94.21% accuracy, respectively,	To predict the fresh properties of SCC	Kina et al. (2021)
Slump flow for high-performance concrete	Classification and regression trees CART, support vector machines SVM, multilayer perceptron MLP and radial basis function neural networks RBF	Usage of bagging (bootstrap aggregating)	SVM, CART, MLP and RBF) and bagging optimize prediction accuracy of the slump flow	To predict the workability	Aydogmus et al. (2015)
Slump flow for ready mix (RMC)	Artificial Neural Networks (ANN) and Genetic Algorithms (GA)	From the actual RMC plant with 560 mix proportions	ANN with GA showed high accuracy	Predict the slump based on	Chandwani et al. (2015)
filling ability, flowability and passing ability of SCC	vector machine approach using the radial basis function (RBF) and polynomial kernels	Experimental data sets	RBF kernel was more accurate compared to polynomial kernel	To predict the fresh properties of SCC	Sonebi et al. (2016)
Slump	Neural network	test data of 187 different concrete mix-designs	99.34% accuracy	Predict slump for high-strength concrete	Öztaş et al. (2006)
Slump and compressive strength	fuzzy logic method	58 and 56	fuzzy logic method is most accurate	To predict the slump and strength	Timur Cihan (2019)
Moisture content	Mel-Frequency Cepstral Coefficients (MFCCs) and SVM for classification	100 sets of concrete specimens	SVM showed acceptable accuracy of moisture prediction	Important for underwater concrete structure to monitor the moisture	Zheng et al. (2019)
Rheological properties	Artificial neural network	200 different mixes, lab	Accepted prediction	Predict the rheology of SCC	Mohebbi et al. (2011)

(Reference: Gamil 2023)

Applications of AI and ML in Mechanical Properties Prediction

Type of concrete	Data sample size	Source of data	ML Model(s)	Accuracy	Output	References
Normal and high-strength concrete	Undefined	Laboratory	Support vector machine (SVM)	SVM can be generalized more effectively than an ANN model.	Elastic modulus	Yan and Shi (2010)
High-performance concrete (HPC)	135	different concrete mixtures	Bagged ANN	R^2 of 0.9278	Compressive strength	Atici (2011)
HPC	1,030	Laboratory	Fuzzy Support Vector Machine Inference Model for Time Series Data (EFSIMT)	R^2 of 0.902	Compressive strength	Cheng et al. (2012)
SCC	Undefined	Experimental data	SVM	SVM showed close prediction with lab-based outcomes	Elastic Modulus of SCC	Cao et al. (2013)
HPC	Undefined	multi-nation data	MLP, SVM, CART, and LR	SVM and MLP are the most accurate	Compressive strength	Chou et al. (2014)
Environmentally friendly concrete	144	from experiments	Gaussian processes regression	R^2 0.98	Compressive strength	Omran et al. (2016)
Fibre reinforced self-compacting concrete	9	concrete mixtures in the laboratory	particle swarm optimization algorithm (PSOA) and ANN	PSOA is more accurate to predict the properties	Mechanical properties	Mashhadban et al. (2016)
Environmental concrete	139	existing sets of data derived from 14 literature.	Artificial Neural Network (ANN)	R^2 : 0.903	Compressive strength	Naderpour et al. (2018)
Normal concrete	49	Literature	Decision tree (DT) model, random forest (RF) model, and neural network (NN)	R^2: DT:0.43 RF:0.68 NN:0.94	Compressive strength	Chopra et al. (2018)
Normal concrete	>10,000	Literature	ANN, SVM, boosted tree, and random forest models	R^2: ANN:0.82, SVM:0.86, BT:0.85 RFM:0.83	Compressive strength	Young et al. (2019)
Normal Concrete	1,030	Literature	Hybrid ML model, random forests (RF) model with the firefly algorithm (FFA)	R2:(0.8664–0.9448)	Compressive strength	Cook et al. (2019)
field-placed concrete	1,681	Colorado Department of Transportation (CDOT)	Random forest ML	R^2:0.80	Compressive strength	DeRousseau et al. (2019)
geopolymer SCC	412	Laboratory data	genetic programming (GEP) and ANN	R^2:0,97	Compressive and split-tensile and flexural strength	Awoyera et al. (2020)
Geopolymer concrete	335	Experimental work	Deep neural network	R^2:0.9927	Compressive strength	Nguyen et al. (2020)
Normal concrete	1,030	Literature	AdaBoost algorithm	R^2 of 0.982 98% accuracy	Compressive strength	Feng et al. (2020)
Recycled aggregate concrete	526	Literature	Random forests (RF) and support vector machine (SVM)	R^2: 0.8709	Modulus of elasticity	Han et al. (2020)
Ultra-high-Performance Concrete (UHPC)	110	Experimental data	Sequential Feature Selection (SFS) and Neural Interpretation Diagram (NID)	80.01% accurate	Compressive strength	Abuodeh et al. (2020)
HPC	1,133	Literature	GBR and XGBoost	R^2 of 0,98	Compressive and tensile strengths	Nguyen et al. (2021)
Normal concrete	207	Literature	decision tree (DT), an artificial neural network (ANN), bagging, and gradient boosting (GB)	DT and ANN gave R2 equal to 0.83 and 0.82	Compressive Strength of Concrete at High Temperature	Ahmad et al. (2021)
Normal concrete	522	Experimental data	Neural Network (ANN), Decision Tree (DT), Support Vector Machine (SVM) and Linear Regression (LR) algorithms	R^2 of 0.86	Compressive strength	Güçlüer et al. (2021)
Normal concrete and fiber reinforced polymers	Dataset 1: 122 Dataset 2: 136	Literature	MLR, SVM, and ANN	R^2: MLR: 0.88 SVM: 0.91 ANN: 0.88	Interfacial bond strength	Su et al. (2021)
Concrete with recycled concrete aggregates	721	Experimental results	Gradient Boosting (GB), Extreme Gradient Boosting (XGB), Support Vector Regression (SVR), and three hybrid models of those single models	R^2 of 0.935	Compressive strength	Quan Tran et al. (2022)
SCC containing Fly Ash and Silica Fume	85	Literature based dataset	ANN and SVM	R^2 of 0.9725	Compressive Strength in SCC	Abunassar et al. (2022)

(Reference: Gamil 2023)

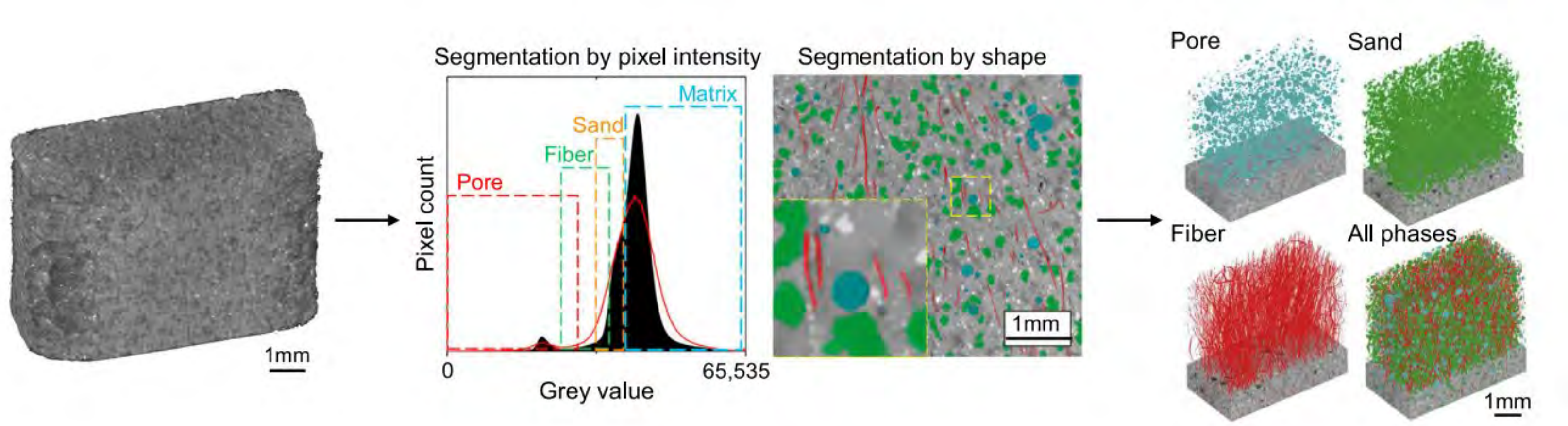
Benefits and Advantages

- Prediction of target properties
  - Accelerate the process of concrete mixture design
  - A solution to the problem of screening optimal mixture proportions that can be further tailored to meet different design specifications
  - Reduce time and labor intensity in trial-batch testing

(Reference: Li et al. 2022)

Benefits and Advantages (Cont'd)

- Increase accuracy
  – Image-based characterization techniques can leverage the power of deep learning to achieve human-level accuracy and beyond



(Reference: Li et al. 2022)

Benefits and Advantages (Cont'd)

- Automation
  - Replace manual observations based bias project management
  - Automatic data analysis and decision making
  - Help managers
    - To better understand the construction project
    - To formalize tacit knowledge from project experience
    - To rapidly spot the project concerns in a data-driven manner
  - More comprehensive picture of the site through various project stages without human interaction

(Reference: Pan and Zhang, 2021)

Benefits and Advantages (Cont'd)

- Risk mitigation
  - AI can monitor, recognize, evaluate, and predict potential risk in terms of
    - Safety
    - Quality
    - Efficiency
    - Cost
  - AI tools have been applied to learn collected data
    - To capture interdependencies of causes and accidents
    - To measure the probability of failure occurrence
    - To evaluate the severity of the risk from both the qualitative and quantitative view
  - Address the limitations of traditional risk analysis

(Reference: Pan and Zhang, 2021)

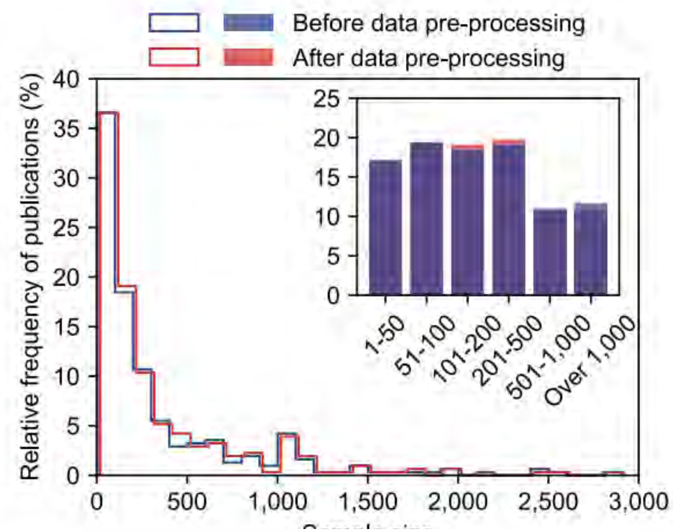
Benefits and Advantages (Cont'd)

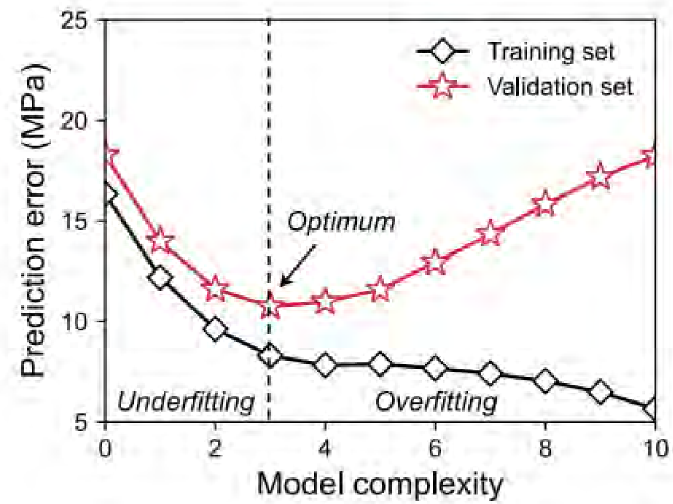
- Improvement and acceleration of computational simulations
  - Combination of AI techniques with kinetic, thermodynamic, and mechanical modeling enables determination of parameters that require extensive experimental data
  - Assists materials design and optimization via high-throughput computational simulations
    - Molecular simulations that are limited by computational cost can immensely benefit from AI acceleration

(Reference: Li et al. 2022)

Challenges and Concerns

- Data challenge
  - Data sparsity
  - High dimensionality
  - Data bias
    - Representation bias
    - Measurement bias
    - Temporal bias
    - Deployment bias

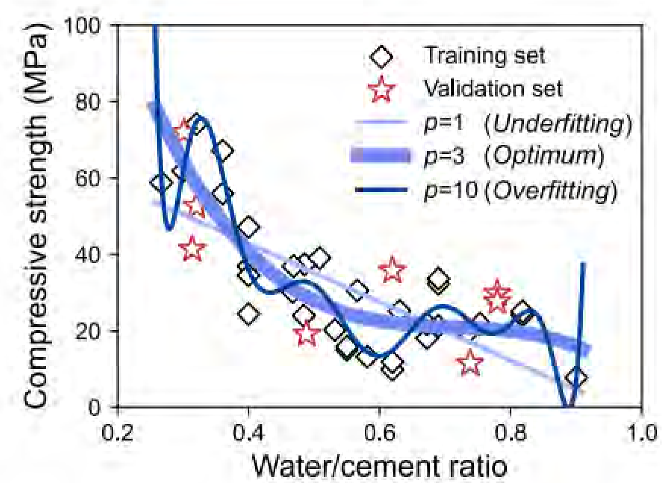


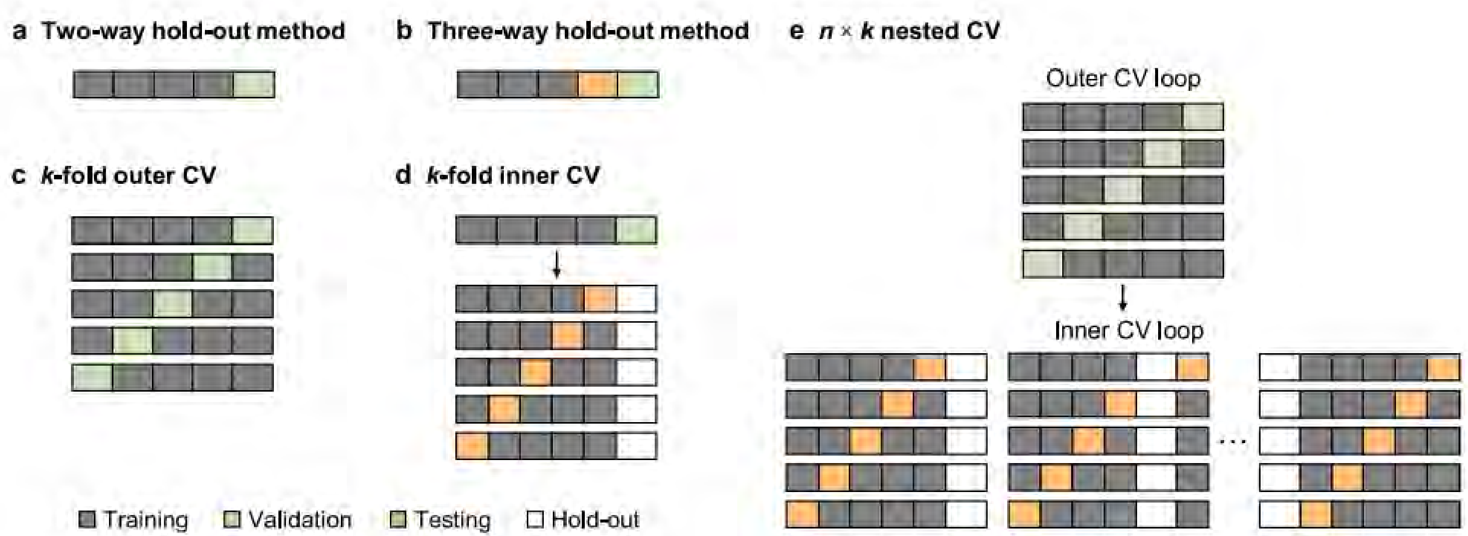


(Reference: Li et al. 2022)

Challenges and Concerns (Cont'd)

- Validation challenge
  - Hold-out method
  - Cross-validation

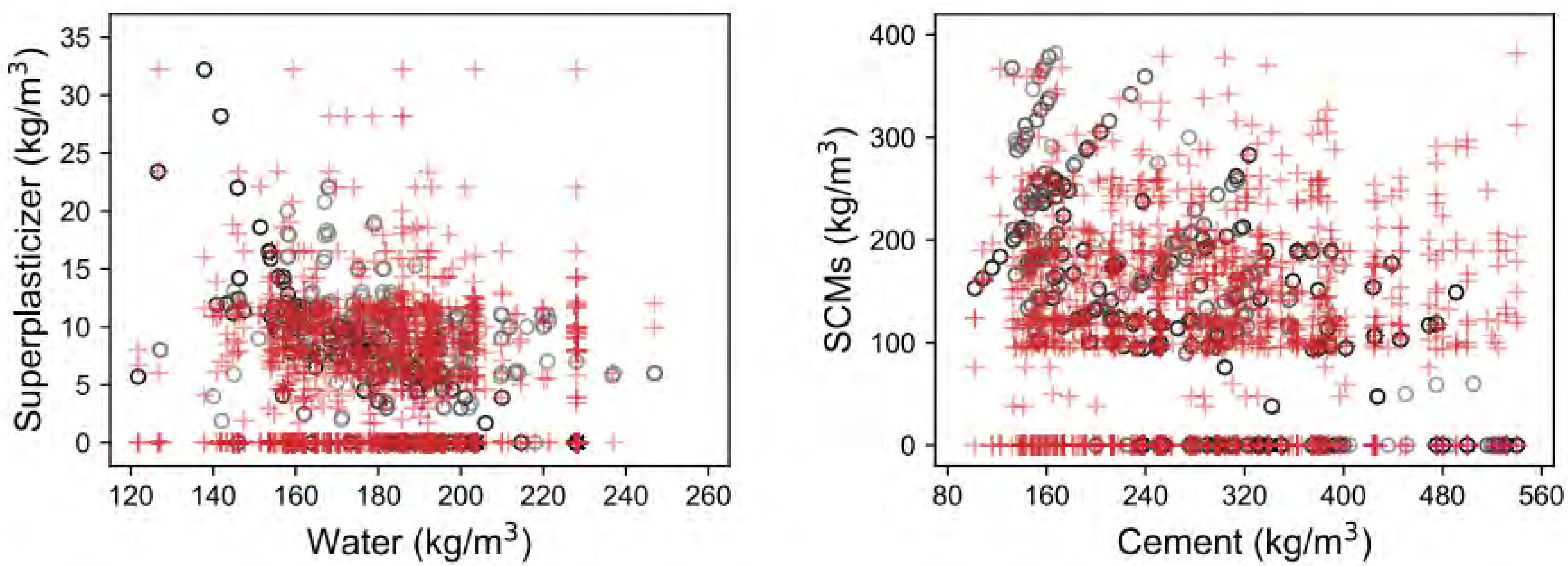




(Reference: Li et al. 2022)

Challenges and Concerns (Cont'd)

- Interpretability challenge
  - Diagnostics
  - Causality



(Reference: Li et al. 2022)

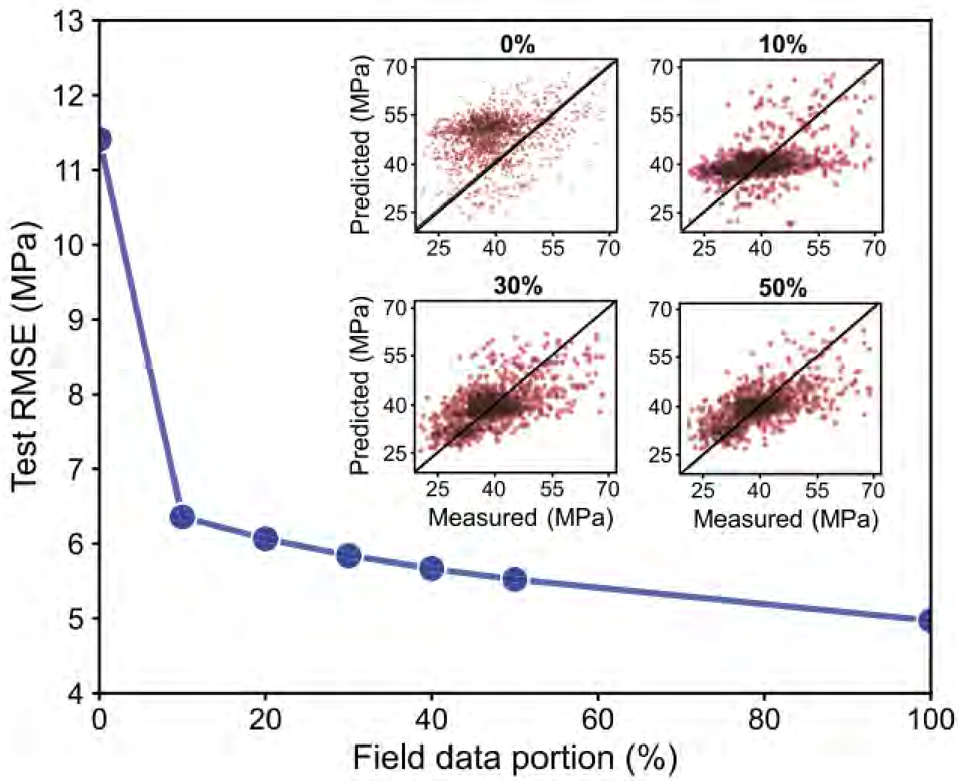
Challenges and Concerns: Directions

- Sharing data and tools
  - Develop new data repositories and broaden the accessibility to existing data
    - FHWA InfoMaterials Web portal: offer characterization data of pavement concrete materials
  - Develop unambiguous standards for reporting and sharing experimental data with consistent categorization across research studies
  - Sharing of computational methodologies (including proposed models, adopted procedures, and source codes) would lower the barriers to data and model verification

(Reference: Li et al. 2022)

Challenges and Concerns: Directions (Cont'd)

- Linking laboratory and field data
  - Hybridization of laboratory and field data for training ML models



(Reference: [Li et al. 2022](#))

Challenges and Concerns: Directions (Cont’d)

- Starting with simple models
  - Simpler models with fewer coefficients or assumptions are preferable to complex one
  - Prediction accuracy and the data accuracy
  - Complex models with less interpretability may only be utilized when additional accuracy gain is significant and necessary

(Reference: Li et al. 2022)

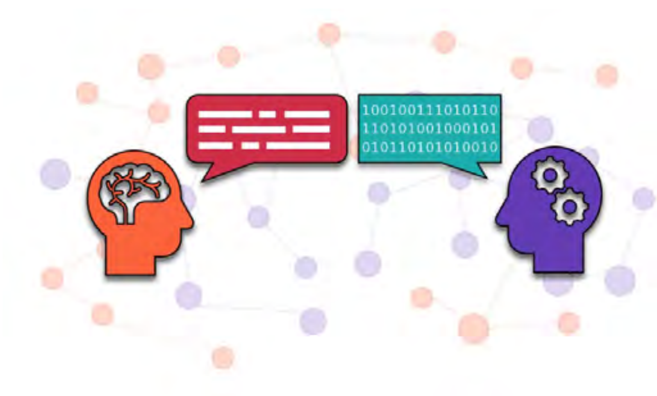
Challenges and Concerns: Directions (Cont’d)

- Knowing when to trust a model
  - Consensus on when to trust the models needs to be reached
    - Generally adopts the 2-sigma (p value ≤ 0.05) rule to validate experimental results
  - Reported performance measures (e.g., accuracy) of ML models should be interpreted with caution
    - Detailed descriptions are required when reporting the models and their performance
    - The performance of a model built for laboratory concrete is not necessarily a good indicator of its performance on field-placed concrete
  - Inability to understand how the algorithms work is a central concern

(Reference: Li et al. 2022)

Challenges and Concerns: Directions (Cont'd)

- Natural language processing (NLP)
  - Concrete mixture design → Immense amount of data in literature
    - Inconsistent data formats → Challenging to manually collect and organize
  - NLP to extract materials data & establish large datasets
  - Extract the process–structure–property–performance relationships by mining text corpora



(Reference: Li et al. 2022)

Challenges and Concerns: Directions (Cont'd)

- Physics-guided
  - Physical laws describing micromechanical responses, degradation mechanisms, and chemical reactivity should be utilized for data preprocessing
  - Adding physics-based loss function terms, pretraining models on data produced by physcis-based models, encoding physical principles into ML architecture design
  - Transforming data driven models into physics-aware surrogate models would
    - Increase interpretability
    - Make more robust and generalizable to field-relevant scenarios
    - Reduce the sample size required for training and computation cost

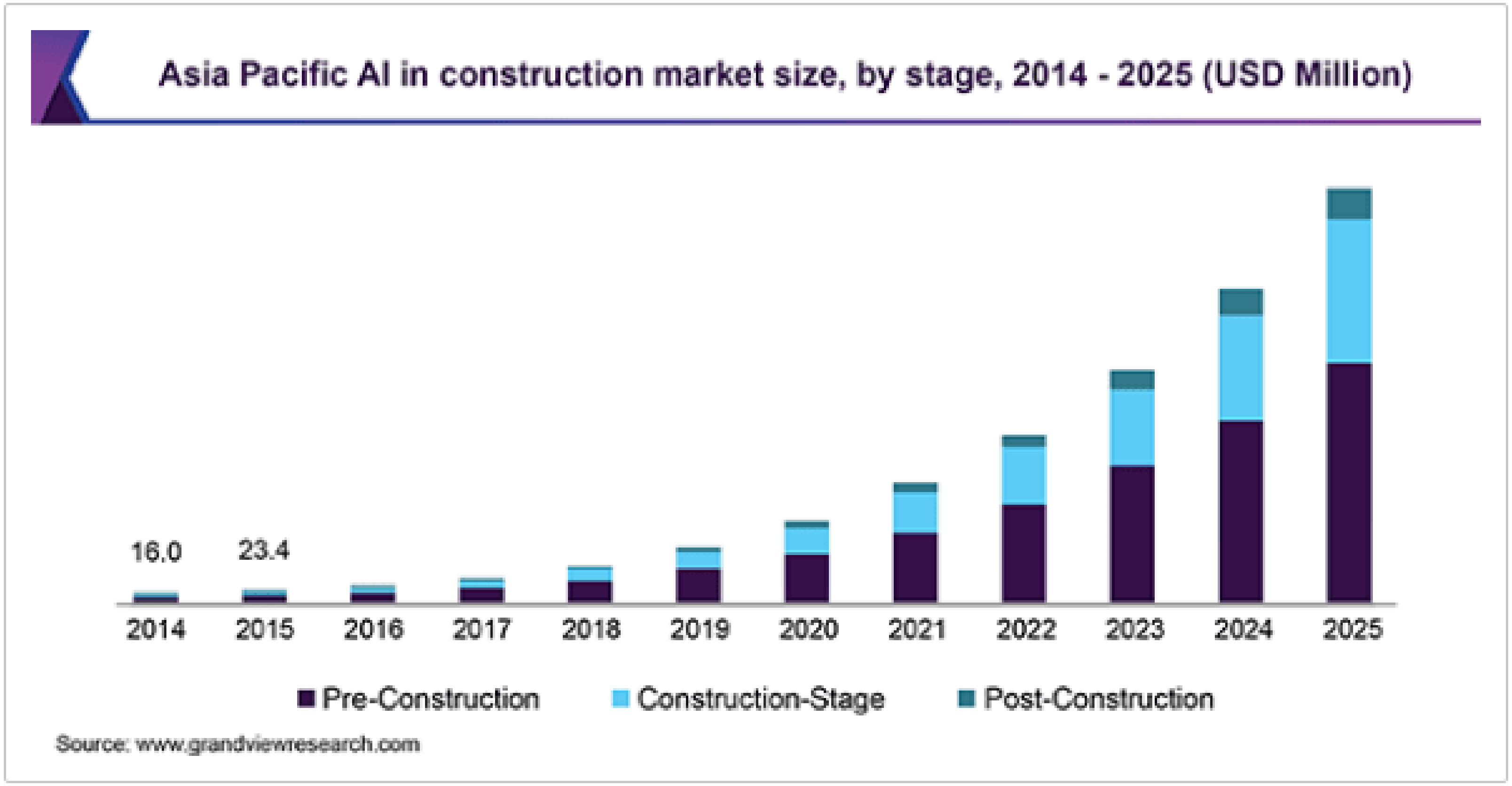
(Reference: Li et al. 2022)

Future of AI in Concrete Design and Construction

- Critical challenge for the concrete industry is the high emission of greenhouse gases

(Reference: Li et al. 2022)

Summary: Overall (Cont'd)



Reference: devtechnosys

Summary: Overall (Cont'd)

- AI-driven design can reduce construction costs by up to 20% and save 50% on material waste
- AI technology in construction and scheduling is expected to save 10-15% on time, resulting in substantial cost savings
- Computer vision applications in construction are expected to increase by over 20%
  - They will help with quality control and safety monitoring
- AI-driven maintenance systems that predict maintenance can reduce costs by up to 30%, and downtime as much as 70%

Reference: devtechnosys