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Can Artificial Intelligence Automate the Microteaching Evaluation?

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Abstract

Purpose. This study aims to describe how automation works in microteaching evaluation by an Artificial Intelligence (AI)-based application through video analysis.

Background. The rapid integration of Artificial Intelligence (AI) into education has transformed assessment and teacher training practices. However, most existing AI applications in microteaching focus on providing feedback or assisting instruction, rather than functioning as autonomous evaluators. This gap underscores the need to understand how automation can systematically operate in evaluating microteaching performance through video analysis, bridging technological capability with pedagogical interpretation.

Method. A qualitative approach was used to elaborate on the explanations of 9 participants selected purposively – including learning experts and AI technology practitioners. In-depth semi-structured interviews were adopted – using instruments curated by education research experts. Thematic analysis techniques, formulated into 6 steps with Nvivo support, were utilized.

Results. The research findings indicate that the process consists of 8 steps. A dataset of human facial expressions and voice intonations embedded into the AI-based application enables the application to identify and categorize students' reactions to learning. This categorization is projected by the adoption and integration of convolutional neural network (CNN) and recurrent neural network (RNN) systems, which can analyze students' verbal and non-verbal aspects in microteaching videos based on the dataset.

Conclusions. The study revealed that automation in microteaching evaluation operates through an eight-stage workflow integrating CNN and RNN systems. This model enables consistent and objective assessment of multimodal cues and offers a replicable foundation for AI-driven teacher evaluation. Further validation through quasi-experimental research is recommended.

1. Introduction

Microteaching is a training approach designed to facilitate prospective teachers in practising teaching skills in a limited and structured manner, using simplified learning scenarios in terms of time, number of students, and complexity of material (Cavanaugh, 2022; de Lange & Nerland, 2018). Through microteaching, prospective teachers are allowed to conduct teaching simulations, receive immediate feedback, and develop critical reflections on their teaching practices (Fernández, 2010; Patcas et al., 2019). This explains why microteaching is urgent in teacher education.

Microteaching has become an integral component of teacher education programs worldwide, providing prospective teachers with opportunities to practice teaching in controlled environments before entering real classrooms (Iliasova et al., 2025a). However, the evaluation of microteaching sessions traditionally relies on manual observation by supervisors or peers, a process that is time-intensive, resource-demanding, and susceptible to subjective bias (İlhan et al., 2023; Iliasova et al., 2025a). As teacher education programs expand and the demand for high-quality, scalable training increases, there is an urgent need for automated evaluation tools that can provide consistent, objective, and timely feedback to prospective teachers while reducing the burden on teacher educators. Historically, microteaching emerged as a response to the need to reduce the risk of errors in real teaching and improve the quality of teacher training, which tends to be abstract and theoretical (Cavanaugh, 2022). Today, microteaching is internationally recognized as a crucial element in teacher education programs, both in face-to-face and online formats (Handayani & Triyanto, 2022; Sezaki et al., 2023).

Microteaching is not merely a complementary innovation, but has become an integral part of teacher education curricula in many countries (Fernández, 2010; Iliasova et al., 2025b). The reliability of microteaching lies in its ability to bridge theory and practice, strengthen pedagogical competencies, and refine communication skills, classroom management, and assessment of learning (Kroeger et al., 2024; Saralar-Aras & Güneş, 2024). Consistent use of microteaching can enhance the quality of self-reflection and peer assessment, accelerate adaptation to the classroom environment, and facilitate the adjustment of teaching strategies according to student characteristics (Crichton et al., 2021; Erdemir & Yeşilçınar, 2021). In practice, microteaching allows prospective teachers to receive feedback from lecturers, peers, and even simulated students, making the self-development process more comprehensive and holistic (Asregid et al., 2023; Tam, 2024).

Recent studies have demonstrated that microteaching bridges theory and practice effectively, strengthening pedagogical competencies and enhancing self-reflection among prospective teachers (Jeon, 2025). Research indicates that microteaching reduces teaching anxiety, builds self-confidence, and facilitates adaptation to classroom environments(Mishra, 2024; Öksüz Zerey & Cephe, 2024). Furthermore, microteaching has proven adaptable to various educational contexts, including online and hybrid formats, and has been successfully integrated with emerging technologies such as video-based learning and flipped classroom approaches (Kokkinos, 2022; Zalavra & Makri, 2022)

Conventionally, microteaching evaluation is conducted manually through direct observation, the use of assessment rubrics, reflective discussions, and verbal or written feedback from instructors or peers (Crichton et al., 2021; Fernández, 2010; Iliasova et al., 2025b). This evaluation typically assesses aspects such as opening skills, material delivery, interaction with students, time management, and closing the lesson (Iswantir & Sesmiarni, 2021; Thangaraju & Medhi, 2023). The advantage of manual evaluation lies in its flexibility and the closeness between evaluators and participants. Evaluators can provide qualitative and contextual assessments, tailored to the individual characteristics of participants, and offer constructive feedback on a personal level (Asregid et al., 2023; Erdemir & Yeşilçınar, 2021). Additionally, the process of collective reflection through peer discussions or debriefings after microteaching sessions serves as a primary growth space for prospective teachers

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(Crichton et al., 2021). However, the manual process requires significant time, effort, and human resources, especially when the number of microteaching participants is very large (Iswantir & Sesmiarni, 2021). The validity of assessment also depends heavily on the experience and objectivity of the evaluator (Thangaraju & Medhi, 2023).

Various challenges have been identified in the practice of manual microteaching evaluation. First, subjective bias in assessment is often unavoidable, whether due to factors such as experience, personal preferences, or time pressure experienced by evaluators (Fitria, 2023; Thangaraju & Medhi, 2023). This subjectivity can affect the consistency and fairness of evaluation results among participants. Second, the limited capacity of evaluators is a major issue in educational institutions with a large number of participants. The observation process, which requires time and high concentration, makes evaluators prone to fatigue, thereby threatening the quality of assessment (Hama & Osam, 2021; Iswantir & Sesmiarni, 2021). Third, delayed feedback. Slow or insufficiently detailed feedback reduces the effectiveness of reflection and improvement of prospective teachers' teaching skills (Erdemir & Yeşilçınar, 2021). Many studies highlight that the time between microteaching practice and feedback is crucial for optimizing learning (Asregid et al., 2023). Fourth, difficulties in standardization. Manual evaluation is prone to variations in assessment standards between evaluators and institutions. The rubrics used are also sometimes not fully tested for reliability and validity (Setyawati & Indiati, 2018; Thangaraju & Medhi, 2023). Fifth, in the context of online microteaching, new challenges arise, such as limitations in non-verbal interaction, technological constraints, and reduced authenticity of learning simulations (Bekereci-Sahin & Aslan, 2025; Sezaki et al., 2023).

Given the various challenges of manual evaluation outlined above, the need for automated evaluation tools has become increasingly evident and urgent. This need aligns with advancements in educational technology and the desire of educational institutions to enhance the efficiency, objectivity, and transparency of the assessment process (Konakbayeva et al., 2025; Saralar-Aras & Güneş, 2024; Winkler-Schwartz et al., 2019). Technology-based automated evaluation tools, particularly those supported by Artificial Intelligence (AI), are believed to provide objective, consistent, and rapid analysis of various aspects of teaching skills. This system is expected to address subjective bias, accelerate feedback, and support large-scale data analysis (Martínez-Comesaña et al., 2023; Memarian & Doleck, 2024; Swiecki et al., 2022).

Additionally, automated evaluation can offer opportunities for personalized learning for prospective teachers based on comprehensive and real-time performance data (Farhood et al., 2024; Laupichler et al., 2023). The use of analytical data enables institutions to identify patterns of strengths and weaknesses and develop more targeted and needs-based professional development strategies (Ruhimat et al., 2025). However, the development of automated evaluation tools requires multidisciplinary collaboration and the readiness of technological infrastructure and human resources who understand how the tools work and how to interpret their results (Joshi et al., 2021; Konakbayeva et al., 2025).

At the same time, the sophistication of AI in analyzing video data has proven capable of mimicking, and even surpassing, human abilities in recognizing, assessing, and predicting human reactions based on voice intonation and facial expressions (Dong et al., 2025; Huiwen, 2025). In the field of education, AI has been applied to evaluate the quality of intonation, articulation, and emotions recorded in verbal interactions between teachers and students (Stošić & Malyuga, n.d.; Zou et al., 2023). This concept positions AI technology as a potential candidate for automating microteaching evaluations through microteaching video analysis.

Using technologies such as computer vision and natural language processing (NLP), AI can analyze micro-expressions, gestures, and vocal patterns and link them to pedagogical parameters

(Alam & Alfawzan, 2024; Chang et al., 2024; Patcas et al., 2019). Recent studies even show that AI can detect a teacher's level of confidence, empathy, and openness solely from analyzing intonation and facial expressions in instructional videos (Konakbayeva et al., 2025; Winkler-Schwartz et al., 2019). This AI capability opens new opportunities for creating automated, precise, and big data-based microteaching evaluation systems (González-Calatayud et al., 2021; Swiecki et al., 2022). Such systems can also present evaluation results in the form of statistical visualizations, improvement recommendations, and individual or collective performance reports (Martínez-Comesaña et al., 2023; Memarian & Doleck, 2024). Beyond learning assessment, similar AI applications have been applied to music assessment, pronunciation, and artistic performance (Huiwen, 2025; Wei, 2023), as well as in the medical field to assess facial expressions and motor performance (Patcas et al., 2019), demonstrating the flexibility and potential of AI across various domains of video-based evaluation.

Although AI's ability to assess intonation, facial expressions, and human performance has been proven across various fields, to date, there is no truly comprehensive and globally standardized AI-based microteaching evaluation tool (Dong et al., 2025; Konakbayeva et al., 2025). Existing studies have only reached the stage of prototype development, pilot studies, or applications in narrower domains such as foreign language pronunciation or emotional expression (Stošić & Malyuga, n.d.; Zou et al., 2023). The main hypothesis that can be formulated is that AI has great potential to automate microteaching assessment, both in terms of verbal and non-verbal skills, through precise analysis of video and audio data (Memarian & Doleck, 2024; Swiecki et al., 2022). This opportunity requires further operational and methodological exploration by experts in education, technology, and ethics to ensure that the tools created truly meet standards of objectivity, reliability, and acceptability (Martínez-Comesaña et al., 2023; Winkler-Schwartz et al., 2019).

While artificial intelligence has demonstrated promising capabilities in analyzing educational videos including assessing intonation, articulation, emotional expressions, and human performance across various fields (Fernández Herrero et al., 2023; Halagatti et al., 2023; Sabha et al., 2025), its application to automated microteaching evaluation remains underexplored. Most existing studies have focused on the theoretical potential of AI for learning assessment or have only reached prototype development stages (Bognár et al., 2024; Luo et al., 2025). To date, there is no comprehensive, globally standardized AI-based tool specifically designed for microteaching evaluation that addresses the practical challenges identified in manual assessment while ensuring reliability, validity, and acceptability in real educational contexts

Ethical issues such as video data privacy, storage security, and algorithmic bias also require serious attention during the development process (Handelman et al., 2019). Additionally, the involvement of faculty members, students, and education practitioners is crucial to ensure that the assessment indicators developed by AI are truly relevant and representative (Laupichler et al., 2023; Ruhimat et al., 2025). This means that the potential for developing AI-based microteaching evaluation tools is vast and will represent a significant leap forward in the professionalisation of teacher education in the future. However, its creation requires interdisciplinary collaboration, further research, and empirical testing across various educational contexts to ensure the tool can be widely implemented and provide tangible benefits for improving educational quality (Konakbayeva et al., 2025; Swiecki et al., 2022; Winkler-Schwartz et al., 2019).

Emerging from this need, this research undertakes a pioneering mission to explore and describe the functioning of an AI-based application designed to automate microteaching evaluation, drawing on insights from both learning experts and AI practitioners. The study aims to bridge the gap between pedagogical theory and technological implementation by examining how artificial intelligence can enhance the accuracy, consistency, and timeliness of microteaching assessments. To realize this objective, the central research question guiding the investigation is: How does the AI-based application-automated microteaching evaluation function?

2. Literature Review

2.1. Microteaching in Teaching Education

Microteaching is a pedagogical approach that has long been recognised as an essential tool in teacher education. Conceptually, microteaching is defined as a training strategy that breaks down the teaching process into small, observable units that can be practised and evaluated on a limited scale, in terms of time, content, and the number of students (Fernández, 2005; Mergler & Donna, 2010). Through short-duration teaching simulations with a limited audience, prospective teachers can systematically and measurably explore, practise, and reflect on their professional competencies (de Lange & Nerland, 2018).

Initially, microteaching developed as a response to the need for safe and controlled practical experience in teacher education. In the digital age, microteaching has evolved into 'Microteaching 2.0,' which combines digital technology and virtual classrooms to further enrich its form, medium, and scope of implementation (Bekereci-Sahin & Aslan, 2025; Ledger & Fischetti, 2020). This transformation not only provides broader access but also facilitates collaborative feedback practices, online peer review, and enhanced self-reflection through various digital platforms (Tam, 2024).

The main objectives of implementing microteaching in teacher education include several fundamental aspects, namely: 1) Enhancing Prospective Teachers' Self-Efficacy: Microteaching provides a space for practising and building confidence in managing classrooms, delivering material, and handling learning dynamics (Mergler & Donna, 2010). 2) Integrating Knowledge and Practice. Microteaching serves as a vehicle for integrating theoretical knowledge gained in lectures with real-world practice, enabling prospective teachers to critically connect concepts, methods, and learning contexts (de Lange & Nerland, 2018; Mandici, 2023). 3) Reflection and Continuous Improvement: Through microteaching, prospective teachers are encouraged to reflect on their teaching experiences, receive feedback from lecturers and peers, and continuously improve their teaching strategies (Asregid et al., 2023; Tam, 2024). 4) Adaptation to Educational Technology: In the digital age, microteaching also aims to familiarise prospective teachers with the use of educational technology, both for planning, implementation, and evaluation of learning (Ledger & Fischetti, 2020).

The effectiveness of microteaching implementation in teacher education can be identified through several key indicators: Systematic Lesson Planning (Fernández, 2005; Mandici, 2023), Communication and Interaction Skills (Hama & Osam, 2021), Simple Classroom Management (Mergler & Donna, 2010), Feedback Reception and Provision (Asregid et al., 2023; Tam, 2024), Use of Media and Technology (Bekereci-Sahin & Aslan, 2025; Ledger & Fischetti, 2020), and Reflection and Self-Development (Seval & Kemal, 2021).

Overall, microteaching has proven to be a transformative medium that places prospective teachers in authentic yet controlled teaching-learning situations, enabling them to develop pedagogical, professional, and social competencies holistically. With adaptations to the dynamics of the times, particularly through the use of technology and reflective practices, microteaching remains relevant as a foundational approach in teacher education across various contexts and countries (Iliasova et al., 2025b).

2.2. The Evaluation of Microteaching

Microteaching has long been recognised as an important pillar in teacher education, particularly as a vehicle for focused, structured, and reflective teaching skills training. However, to ensure its effectiveness and contribution to the professional development of prospective teachers, a comprehensive, layered, and contextual evaluation process is required (Ralph, 2014; Thangaraju & Medhi, 2023). Through an in-depth examination of Thangaraju & Medhi's (2023) work, microteaching evaluation is understood as a series of assessment activities conducted on micro-scale teaching practices, encompassing aspects of planning, implementation, and learning reflection. Its purpose is not only to measure the achievement of pedagogical skills but also to stimulate a continuous process of self-improvement (Iliasova et al., 2025b). This evaluation includes formative and summative assessments and may involve lecturers, peers, and self-reflection by the trainee (Erdemir & Yeşilçınar, 2021). The primary function of microteaching evaluation is as a diagnostic tool to identify the strengths and weaknesses of prospective teachers, a means of providing feedback for improvement, and an instrument for fostering a culture of reflection and professionalism within the teacher education environment (Baseer et al., 2020; Ralph, 2014).

Microteaching evaluations are conducted using various instruments, including lecturer and peer assessment forms, video recordings for self-assessment, and reflective discussions after practice. (Vander Kloet & Chugh, 2012) emphasise the importance of designing evaluation instruments that are not merely administrative but also capable of accommodating the creative, innovative, and contextual dimensions of teaching practice. Evaluation instruments should not only measure the achievement of technical aspects, such as the clarity of material delivery or classroom management, but also affective dimensions such as motivation, empathy, and the ability to adapt to classroom changes.

(Sezaki et al., 2023) Their systematic review shows that the use of online technology—such as video conferencing platforms and Learning Management Systems (LMS)—expands access, enriches the variety of feedback, and increases the objectivity of evaluation through digital evidence that can be reviewed. Through a review of various scientific publications, it is known that the dimensions of microteaching evaluation in teacher education consist of six dimensions: 1) Instructional Planning Skills, which refers to the readiness of prospective teachers to develop learning objectives, steps, methods, and evaluation instruments (Thangaraju & Medhi, 2023). 2) Communication and Presentation Skills, which assess the clarity of instructions, articulation, voice intonation, and the use of non-verbal language during teaching practice (Bilen, 2015). 3) Classroom Management, meaning the ability to manage student dynamics, time, and responses to unexpected situations in the microteaching classroom (Ralph, 2014). 4) Innovation and Adaptation, or the ability to apply technology, learning media, and pedagogical innovations during microteaching (Sezaki et al., 2023). 5) Reflection and Self-Development, meaning the extent to which prospective teachers can critically reflect on their practices, including their readiness to receive and utilise feedback (Crichton et al., 2021; Erdemir & Yeşilçınar, 2021). And 6) Quality of Interaction and Student Engagement, which involves assessing efforts to build interpersonal relationships, motivate participation, and create an active learning environment (Vander Kloet & Chugh, 2012).

In addition to dimensions, one essential aspect of microteaching evaluation is the feedback mechanism that prospective teachers receive from various sources. (Baseer et al., 2020) show that micro-feedback workshops can change the perceptions and practices of lecturers and students regarding the evaluation process—emphasising the importance of specific, constructive, and immediate feedback. Peer feedback and self-assessment are also crucial in fostering a reflective culture, strengthening empathy, and building critical awareness of each individual's professional practices (Crichton et al., 2021; Erdemir & Yeşilçınar, 2021). However, several challenges still arise in microteaching evaluation, including the potential for subjective bias in peer assessment, time constraints, and the immaturity of evaluation instruments that tend to be normative and less adaptive to contemporary needs (Iliasova et al., 2025b). In light of these challenges, (Sezaki et al., 2023) advocate for the dynamic updating of microteaching evaluation, including through technological innovation.

2.3. The Challenges of Microteaching Practices Manually

Microteaching is an important tool in the professional development of prospective teachers, providing a safe and controlled space for teaching practice on a limited scale. However, when microteaching evaluation practices are still carried out manually—that is, without technological support and relying entirely on direct observation, paper assessment forms, and verbal feedback—several significant challenges arise that affect the objectivity, effectiveness, and sustainability of the learning process for prospective teachers. These challenges include, but are not limited to, the eight issues we have identified.

First, the limitations of the objectivity and subjectivity of assessors. Evaluations are often heavily influenced by the personal perceptions of lecturers or peers, making them prone to bias and subjectivity, whether in the form of preferences for certain characteristics or a tendency to generalise performance based on previous practices (Erdemir & Yeşilçınar, 2021; Thangaraju & Medhi, 2023). (Hama & Osam, 2021) highlight that, in many cases, manual assessments tend to be normative and fail to capture innovative, adaptive, or creative approaches that are crucial in 21st-century education.

Second, limitations in documentation and traceability. The absence of digital records in manual evaluations results in inadequate documentation of feedback. Paper forms are easily lost or damaged, and verbal feedback is often not heard or fully understood by participants (Asregid et al., 2023). This impacts the limited opportunities for longitudinal reflection, making it difficult for participants to review their progress or achievements over time (Erdemir & Yeşilçınar, 2021).

Third, the time and efficiency of the evaluation process. Manual evaluation processes are highly time-consuming for both instructors and students. Observations must be conducted alternately, assessments must be recorded one by one, and feedback is often hindered by time constraints in the classroom (Davids, 2016; Thangaraju & Medhi, 2023). This limits opportunities for in-depth discussion, reflection, and detailed exploration of feedback.

Fourth, resistance to reflection and critical feedback. Many microteaching participants, especially those unfamiliar with a culture of reflection, feel awkward or defensive about open criticism given directly (Asregid et al., 2023; Erdemir & Yeşilçınar, 2021). Time constraints and an occasionally nonconductive classroom atmosphere often make the reflection process merely a formality, failing to foster meaningful learning. (Davids, 2016) also notes the tendency of manual microteaching to merely replicate conventional teaching practices without room for experimentation and innovation.

Fifth, there is a lack of support for differentiation and innovation. Manual evaluations, which are generally based on standard rubrics, often fail to accommodate the diversity of teaching styles, learning contexts, and individual needs of prospective teachers (Hama & Osam, 2021). Standardised evaluation forms tend to limit innovation, so that different teaching practices are considered 'off track' and rated poorly, even though diversity is the key to creativity and responsiveness in modern education (Setyawati & Indiati, 2018).

Sixth, the potential for errors or 'misconceptions' in assessment. (Setyawati & Indiati, 2018) emphasise that time constraints and the burden of manual assessment often lead instructors/peers to evaluate only superficial aspects, failing to capture the deeper misconceptions experienced by participants. As a result, microteaching participants may develop blind spots in the essential pedagogical competencies they are striving to master.

Seventh, limitations in collaboration and peer feedback. Although microteaching ideally encourages peer feedback, manual practices often result in less structured collaboration processes. Peer feedback tends to be limited to spontaneous comments rather than data-driven or recording-based discussions (Asregid et al., 2023; Erdemir & Yeşilçınar, 2021). This hinders the creation of an empowering learning community.

Finally, a lack of integration of technology and modern reflective practices. As noted by (Sezaki et al., 2023) and (Bekereci-Sahin & Aslan, 2025), technology-based microteaching has proven capable of enriching the evaluation process through video recordings, asynchronous feedback, and more in-depth reflective analysis. The absence of technology in manual evaluation leaves prospective teachers behind in 21st-century skills and deprives them of learning opportunities from digital experiences.

Thus, manual microteaching evaluation practices do have historical value and valuable initial contributions to teacher education. However, challenges, including subjective bias, weak documentation, low efficiency, limited innovation, and resistance to critical reflection, demand a transformation toward a more collaborative, technology-based, and reflective evaluation approach. By systematically addressing these challenges, teacher education can become more adaptive to the demands and realities of contemporary learning.

2.4. The Need for Automation in Microteaching Evaluation

In the era of the Fourth Industrial Revolution and accelerated digital transformation, the practice of microteaching evaluation in teacher education faces urgent demands for change. Conventional manual evaluation has proven to have fundamental limitations, such as subjective bias, scalability constraints, slow feedback, and inefficiency in terms of time and resources (Azrai et al., 2020). In line with the development of AI, the need to automate microteaching evaluation has now become a strategic agenda in efforts to achieve effective, efficient, and adaptive education in response to the challenges of the times. We have synthesised five fundamental reasons why microteaching evaluation must evolve towards automation.

First, the complexity of microteaching evaluation and the limitations of manual evaluation. Microteaching practices require the assessment of various aspects of prospective teachers' competencies, ranging from communication skills and mastery of subject matter to classroom management and nonverbal aspects, such as gestures and voice intonation. Manual evaluation often fails to address these dimensions holistically or objectively due to time constraints, evaluator capacity, and limited space for self-reflection (Konakbayeva et al., 2025; Mu et al., 2025). Manual evaluation systems also struggle to detect learning patterns and behavioural changes over time, leading to reactive and often misdirected improvement interventions.

Second, the potential and role of AI in evaluation automation. The adoption of AI in the microteaching evaluation process enables more precise, faster, and objective data analysis. AI can analyse microteaching videos, identify behavioural patterns, assess the quality of interactions, and even map teachers' competency development in real time (Tang et al., 2023; Winkler-Schwartz et al., 2019). Machine learning and pattern recognition technologies can also identify the strengths and weaknesses of individual teacher candidates, resulting in feedback that is more personalised, prescriptive, and promotes continuous professional growth (Memarian & Doleck, 2024; Swiecki et al., 2022). AI not only offers speed in providing feedback but also ensures that the evaluation process is free from personal bias and can be conducted at scale without compromising the quality of assessment (Laupichler et al., 2023; Martínez-Comesaña et al., 2023). Automated evaluation systems can be integrated with both online and offline learning systems, making them flexible and easily accessible to various parties.

Third, the need to optimise resources and improve quality. Automating microteaching evaluation directly reduces the administrative burden on lecturers, speeds up the data processing of assessments, and allows for the allocation of time and energy to more meaningful pedagogical activities, such as mentoring or developing learning innovations (Azrai et al., 2020; Konakbayeva et al., 2025). AI-based evaluation systems can operate 24/7, enabling microteaching practices and feedback to be conducted asynchronously, without being constrained by time or location (Saralar-Aras & Güneş, 2024). Recent research also shows that AI-based automated feedback can enhance the confidence and instructional quality of prospective teachers, as the feedback provided is more specific, detailed, and tailored to individual needs (Konakbayeva et al., 2025; Mu et al., 2025). AI can also identify non-verbal aspects that are often overlooked in manual evaluations, such as the use of gestures, expressions, or voice patterns in teaching (Winkler-Schwartz et al., 2019).

Fourth, the potential positive implications for education management and supervision. At the institutional level, the automation of microteaching evaluation is a strategic solution to address human resource limitations, expand the scope of supervision, and support data-driven policies as a vehicle for teacher professional development (Farhood et al., 2024; Ruhimat et al., 2025). Automation can also strengthen the accountability of the education system by providing valid, reliable, and audit-ready digital records, thereby supporting transparency in teacher training and promotion. Thus, the urgency of automating microteaching evaluation is not merely based on efficiency demands but also on the need to build a teacher education ecosystem that is data-driven, accountable, responsive, and adaptive to technological changes.

2.5. The Potential of Artificial Intelligence Utilization in Microteaching

Amidst massive digital transformation, AI has emerged as a strategic solution in overcoming various conventional obstacles in microteaching assessment, particularly through the integration of automatic video analysis. This development marks a paradigm shift from subjective and manual assessment towards data-driven, real-time, and more accurate multidimensional evaluation.

Considering that microteaching has long been a central instrument in the training and assessment of prospective teachers. However, the traditional assessment process based on manual observation, in addition to being time-consuming and resource-intensive, is prone to subjective bias, limitations in documentation, and low consistency among assessors (Konakbayeva et al., 2025). In this context, AI—particularly through video analysis technology—holds significant disruptive potential. By automatically analysing microteaching video recordings, the assessment process becomes more objective, standardised, and capable of capturing dimensions of teacher performance that have been difficult for humans to observe, such as nonverbal gestures, intonation, and the quality of verbal-nonverbal interaction (Mu et al., 2025; Winkler-Schwartz et al., 2019).

AI in microteaching video assessment can utilise computer vision algorithms, speech recognition, and natural language processing (NLP). Through computer vision, AI can detect facial expressions, body posture, movements, and communicative gestures, as applied in facial aesthetics assessment (Alam & Alfawzan, 2024; Patcas et al., 2019). On the other hand, speech recognition and NLP enable AI to evaluate vocal quality, intonation, language fluency, and the clarity of instructions given by teachers (Dong et al., 2025; Huiwen, 2025). For example, a study by Huiwen (2025) shows that AI software has been able to automatically correct intonation errors, providing granular feedback on vocal performance and presentation. In language teaching, AI has proven effective in evaluating students' pronunciation, accent, and clarity of speech (Stošić & Malyuga, n.d.; Zou et al., 2023). These findings are parallel to the study by Dong et al. (2025), which highlights AI's ability to detect phonetic and prosodic errors that are often overlooked by human assessment.

The Advantages of AI-Based Video Microteaching Assessment Automation lie in several strategic advantages in evaluating microteaching through video. First, regarding the potential for increased objectivity. AI can reduce human bias and enhance consistency in evaluations across time and participants, leading to greater objectivity in assessment (Martínez-Comesaña et al., 2023; Swiecki et al., 2022). Second, scalability and efficiency. AI can analyse thousands of microteaching videos in a short time, expanding the scope of evaluation without increasing the burden on human resources (Huang et al., 2023; Kim et al., 2022). Third, data granularity. Through frame-by-frame analysis and voice detection, AI can provide highly detailed feedback, ranging from interaction quality to specific nonverbal tendencies (Mu et al., 2025; Winkler-Schwartz et al., 2019). Fourth, customised and adaptive feedback. AI, including technologies such as ChatGPT, can generate personalised feedback that responds to the specific needs of each prospective teacher and supports interactive dialogue-based learning (Lyanda & Owidi, 2025). Fifth, Multimodal Integration. AI can combine visual, auditory, and even textual data to assess teaching competencies comprehensively and contextually (Chang et al., 2024; Jeon, 2025).

The discussion on AI automating microteaching evaluation through video analysis—as proposed by this study—is related to several recent studies. (Konakbayeva et al., 2025) illustrate that the use of AI in microteaching lesson studies can enhance prospective teachers' confidence and instructional quality through automated video assessment supported by real-time feedback. In the medical field, Winkler-Schwartz et al. (2019) utilised AI to assess surgical skills using video simulations, achieving accuracy levels surpassing those of human evaluators. In the context of language education, AI speech evaluation systems have been widely implemented in Asia, promoting equitable assessment of pronunciation and speaking skills (Zou et al., 2023). These three studies support the statement by (González-Calatayud et al., 2021) that the integration of AI in assessment in education generally strengthens validity and reliability, as well as accelerates the cycle of reflection and self-improvement among students and teachers.

Based on the synthesis of the above studies, it can be asserted that integrating AI into specific assessment activities through video analysis can fundamentally revolutionise the paradigm of educational evaluation. This is because AI has the potential to become an augmented assessor that not only enhances the objectivity and scalability of assessment but also enriches the learning experience and reflection of prospective teachers through data-driven, multimodal, and adaptive feedback. Theoretically, AI enables the realisation of assessment for learning that is more dynamic, personalised, and empowering (González-Calatayud et al., 2021; Lyanda & Owidi, 2025). However, AI-driven evaluation automation has not been applied to microteaching in teacher education. The success of this transformation is believed to depend heavily on collaboration between education-sector experts and AI technology practitioners. Therefore, as a pioneering step in this transformation, the operational mechanism of the microteaching evaluation model automated by an AI-based application through video analysis must be comprehensively described. This research aims to address this necessity.

3. Methodology

3.1. Research Design

This study uses a qualitative approach (Kushnir, 2025) with a phenomenological design (Anastassiou, 2017). The design is intended to obtain a strong epistemic and contextual understanding of specific small entities and to explore how the microteaching evaluation model can be automated by AI-based applications.

3.2. Data Collection Instrument

The primary data collection instrument for this study was a semi-structured interview protocol comprising 11 open-ended questions designed to explore participants' understanding and experiences with AI-based automation of microteaching evaluation. The instrument was developed through a systematic process following the guidelines for qualitative interview protocol development (Kallio et al., 2016).

The initial protocol was constructed based on:

1. A comprehensive literature review on microteaching evaluation frameworks and AI applications in educational assessment

2. The research question's focus on using AI to analyze facial expressions and conversation voices in microteaching videos

3. Theoretical frameworks from both the educational assessment and AI technology domains

To ensure the instrument’s trustworthiness and credibility, several measures were implemented. First, the initial interview protocol was reviewed by an education research expert with extensive experience in qualitative methodology and educational assessment. The expert assessed the protocol’s content validity, alignment with the research objectives, clarity and appropriateness of the questions, and the logical flow and potential to elicit rich and detailed responses. Afterward, a pilot test was conducted with three participants, comprising two learning-expert lecturers and one AI technology practitioner, to evaluate the instrument's effectiveness. The pilot study examined question clarity, participant comprehension, and the overall flow and duration of the interview, while also testing the recording and transcription process. Based on feedback from both expert review and pilot testing, the protocol was refined by clarifying ambiguous terminology, improving the question order to ensure better logical progression, adding targeted probes related to the technical aspects of AI applications, and ensuring cultural and contextual relevance for Indonesian participants. During data collection, member checking was employed, allowing participants to clarify or expand upon their responses and validate summary interpretations. These combined procedures adhere to the established criteria for rigor in qualitative research (Lincoln & Guba, 1985; Tracy, 2010), emphasizing the credibility, dependability, and confirmability of the data collection process.

3.3. Interview Design

The in-depth interview model was chosen because it allows for detailed exploration of participants' understanding and relevant experiences regarding the potential for microteaching evaluation models to be automated by AI-based applications. This choice aligns with Anastassiou's (2017) observation that the in-depth interview model in qualitative research enables researchers to gain deeper insights that are often overlooked in quantitative research.

The research question focuses on how to use Langkah to create AI-based applications with sophisticated, renewable capabilities, to analyse students' facial expressions and conversation voices from video, automating microteaching evaluation. The video in question is a recording of microteaching activities at a university. Eleven open-ended and structured questions were used to elicit detailed statements from participants, who were then given follow-up questions to deepen their understanding. An education research expert curated the interview protocol's structure and reliability as a data collection instrument. Further testing based on a pilot project was conducted involving two lecturers and one technology practitioner. After this testing phase, the interview protocol was developed to ensure clarity and effectiveness. This aligns with Rutledge and Hogg's (2020) assertion that advocating for the refinement of interactive interview protocols is necessary to enhance the accuracy of data collection in line with research objectives.

3.4. Sampling and Recruitment

In accordance with the established research objectives, the required sample or participants are learning experts and AI technology practitioners. The purposive sampling technique was used (Lichtman, 2023; Palys, 2024) to ensure that the selected participants had a strong understanding and expertise, as well as relevant experience to support their explanations of microteaching and AI technology. To explain sample filtering, Table 1 sets out the inclusion and exclusion criteria.

Table 1. Inclusion and exclusion criteria

Categories	Inclusion	Exclusion
Learning Expert	15 years or more of experience in the educational field	Not yet 15 years of experience
	Has published more than 20 research papers on learning in Scopus-indexed journals or books.	20 relevant research publications or fewer
	Has been a lecturer in microteaching for more than 5 years	Less than 5 years of experience
	Have works that demonstrate the use of AI in learning assessment studies	No relevant works
Artificial Intelligence (AI) Practicionare	Over 5 years of experience an information and communication program or application development	5 years of experience or less
	Have evidence of AI-based applications or programmes that can analyse videos or images.	No evidence of relevant work

Recruitment for the learning expert sample category was conducted via messages sent to lecturers' email addresses at seven leading universities in Indonesia. Meanwhile, recruitment of the AI practitioner sample category was conducted through messages sent to five companies and nine AI-based application developer communities. The recruitment messages were distributed along with a Google Form link for filling out. Those who responded and expressed willingness to become informants were then selected purposively according to the criteria in Table 1. Of the 17 applicants who expressed interest, only 9 met the inclusion criteria and were selected. This sampling strategy aimed to capture participants' perspectives on the potential of automated microteaching evaluation using AI (A. J. Bingham, 2023; G. E. Bingham et al., 2022). While diversity of perspectives was nearly guaranteed from the outset, this diversity could enrich the substance of the research report. Thus, the sample size does not represent a specific population as in quantitative studies. On the one hand, this aspect is a certain limitation. However, at the same time, this purposive sampling promises data that aligns with the topic being deeply explored by this research.

3.5. Informants Description

The nine informants in this study consisted of two categories. The first category comprised three learning expert lecturers from the Indonesia University of Education (UPI), Jakarta State University (UNJ), and Yogyakarta State University (UNY). The second category consists of six AI practitioners from five companies and one application development community in Indonesia. The oldest is 51 years old, while the youngest is 25 years old. They all represent relevant professional backgrounds and meet the inclusion criteria. Each offers a unique perspective on the concept of microteaching and the potential of AI in analysing videos. These diverse experienced professionals bring their wealth of understanding and experience to the discussion, particularly regarding microteaching design and various examples of AI applications with varying levels of complexity.

3.6. Ethical Clearance

To meet academic and cultural ethical standards, each interview was recorded only with the participants' consent. Interviews were conducted only on agreed-upon schedules. Their voices are disguised, and their identities are kept confidential. These measures provide comfort and flexibility for participants, enabling in-depth dialogue, transcription, and analysis. The structured yet flexible nature of the interviews creates a space for in-depth dialogue with participants, supporting the collection of comprehensive, detailed data.

3.7. In-depth Interview Process

The in-depth interview process lasted three months, although it was initially planned to last only one month. This duration exceeded the initial plan because efforts to obtain data continued until the data reached a level of saturation and clarity, in accordance with the principle of data saturation in qualitative research. Achieving clarity or saturation is crucial to ensuring the integrity and depth of research findings. The consequence of this integrity is that data collection can only be stopped when no additional data emerges to further develop the thematic framework (Saunders et al., 2018). In other words, this is a natural cessation of data collection. Historically, this concept was first proposed by Glaser and Strauss (2017) as a qualitative parameter to assess the sufficiency of data collected through a systematic, repetitive process.

3.8. Data Analysis

Data analysis follows a 6-step thematic analysis process for qualitative educational research, based on the model by Ahmed et al. (2025). The first phase is data familiarisation. The researcher immerses themselves in the raw data, which consists of interview transcripts and relevant previous research findings. In this first step, the researcher reads and rereads the material to engage actively with it, noting down initial ideas and reflective memos that can support initial insights into the data. The second phase is the creation of initial codes. The researcher systematically identifies codes from the entire dataset, where each code summarises a specific segment of the data. In this second step, NVivo software is used, given its suitability for qualitative data analysis (Limna, 2023).

The third phase is theme exploration. In this phase, the researcher begins to group codes into themes—as broader data segments that encompass previously existing codes and connect to the research questions. Interpretive thinking between themes and research questions is used in this step. Next is the fourth phase, theme review. Themes are reviewed to ensure coherence, both between themes and research questions, and between one theme and another, to identify similarities and differences among themes. Researchers return to the raw data to ensure an accurate representation of the themes that have been constructed. This step leads to the merging, separation, or removal of certain themes after review.

The fifth phase is the establishment and naming of themes. After the fourth step is completed, the researcher refines the essence of each theme and explains how each theme relates to the research question, as the focus of the research. Once established, the themes are named using concise diction or phrases—supported by detailed descriptions to enhance clarity and accompanied by supporting quotes from the various literature reviews used. Finally, the sixth phase is the preparation of the report. In this final stage, the researcher presents the findings through a coherent descriptive narrative. The report includes visualisations of codes and themes, as well as detailed explanations based on the data extraction process – including coherent statements from participant 1 (P1) to participant 9 (P9) and analytical comments. This constructs an answer to the question, 'How does automation work in microteaching evaluation by AI-based applications through video analysis?'

4. Findings

This study involved nine participants divided into two categories with different backgrounds and competencies. The first category consisted of three lecturers who were experts in learning, namely P1, P2, and P3. They came from three leading universities in the field of education with good reputations in Indonesia. They have nationally recognised academic reputations, are actively involved in curriculum development and teacher education practices, and have tested various innovative learning methods. The second category consists of six AI technology practitioners, namely P4–P9, who have extensive experience in computer vision, machine learning, application development, and technology-based learning system development.

The participants' ages vary significantly—from the youngest at 25 years old, who has only been in the AI industry for a few years but has already led international-scale projects, to the most senior at 51 years old, with decades of experience in both education and technological development. This diversity offers a rich perspective, encompassing the insights of the digital generation alongside the depth of experience of those who have witnessed technological transformation from the pre-Internet era to the AI era. The interviews were conducted in-depth between 1 May and 1 August 2025, both in person in campus discussion rooms and virtually using video conferencing platforms. Each interview was recorded, transcribed, and analysed to identify key themes in line with the research objectives. First, the research findings were grouped according to participants' perspectives on transparency in the process of reconstructing the identified themes.

4.1. Learning Expert Perspective

The three expert teacher-educators who participated in this study unanimously agreed that current microteaching evaluations suffer from fundamental weaknesses that necessitate technological intervention. P1, a senior lecturer with over two decades of experience in teacher education, highlighted the persistent problem of subjectivity in assessment.

> *"Microteaching assessments have often fallen into the trap of subjectivity. I have witnessed cases where a student received a low score not because of poor teaching quality, but because of a strained personal relationship with the assessor. An automated system could cut off that chain of bias." (P1, May 3, 2025)*

For P1—regardless of the debates surrounding the use of technology in education—technology is not a threat to the lecturer's role, but rather an instrument to ensure fairness and consistency in evaluation. His experiences as a witness to unjust microteaching assessments have prompted critical reflection on the necessity of safeguarding objectivity in teacher training evaluation. His statement in a follow-up interview reinforced this position:

> *"Subjectivity in microteaching assessment is dangerous. Such practices produce false evaluation results. Worse still, they can lead to parallel errors in teacher education. For instance, a lesson planner might make use of the false data." (P1, June 7, 2025)*

P1 views automation as a potential collaborative partner capable of standardizing assessment processes without erasing the humanistic dimension of lecturer guidance. On the other hand, P2—who, in addition to teaching, also holds a structural position in the faculty—focused on time and energy efficiency. In his daily experience, he frequently observes lecturers exhausted from evaluating dozens or even hundreds of microteaching sessions each semester.

> *"If we assess every microteaching session manually, lecturers will exhaust their energy just watching and commenting. That time could instead be devoted to mentoring students, developing teaching methods, conducting research, or engaging in other important academic tasks. So automated evaluation does not mean removing the lecturer's role—it makes it more strategic." (P2, May 5, 2025)*

P2 emphasized that freeing lecturers from prolonged, labor-intensive assessment workloads would create space for more meaningful student mentorship and for research activities critical to advancing educational practice. P1's statement that "the workload of lecturers in Indonesia, including assessment duties, is extremely time-consuming" (P1, June 7, 2025) further aligns with P2's perspective.

Meanwhile, P3 offered a long-term strategic perspective, envisioning the potential of archiving and conducting longitudinal analyses of microteaching videos:

> *"Imagine if we had a database of students' microteaching videos spanning years. It would be a goldmine for research—tracking the progression of prospective teachers' abilities from their first semester*

to graduation. We could also examine and identify patterns in learners' reactions during microteaching sessions." (P3, June 12, 2025)

For P3, a microteaching video database could serve as a vital resource for continuous training in assessment practices. He also noted that such archives could establish quality benchmarks for graduates across cohorts, while serving as training material for lecturers to better attune themselves to students' evolving competencies.

All three experts concurred that automating microteaching evaluation aligns with the demands of the times. P2 captured this sentiment succinctly, contrasting the need for academic reflection with the imperative to adopt technology wisely—especially in light of the characteristics of students as digital natives:

"Our students are digital natives. If their evaluations still rely on paper and subjective opinions, it feels like we've missed the train." (P2, May 5, 2025)

From these various perspectives, their views converge on four primary reasons for automating microteaching evaluation. First, reducing subjectivity in assessment. Second, increasing the efficiency of time and energy usage. Third, building a longitudinal database for teacher education. Fourth, adapting teaching evaluation to technological developments.

4.2. AI Practitioner Perspective

While the academic experts emphasized why automation is necessary, the AI practitioners elaborated on how such a system could be constructed. P4, a computer vision engineer with experience in multiple international facial detection projects, explained that the initial stage involves building a dataset of human facial expressions:

"The first thing we need is a facial dataset. But don't think creating a facial dataset is easy. The difference between a confused expression and an understanding one can be very subtle—especially if the person is trying to maintain a composed demeanor. We need datasets of confused faces, understanding faces, enthusiastic faces, even sleepy faces, all captured under varying lighting conditions and from different angles." (P4, May 20, 2025)

This statement underscores not only the role of facial datasets as the nonverbal data required to create an automated microteaching evaluator application, but also the inherent complexity of accurately categorizing diverse facial expressions. P5 continued the discussion by addressing the equally critical audio dimension, stressing that voice intonation is a verbal indicator that must be handled with precision in such an application.

"If someone's voice rises at the end of a sentence, it could indicate uncertainty—or it might just be their speaking style. This is where AI faces a challenge. We need datasets of confident, skeptical, and unfocused voice intonations, and then train the system to distinguish between them." (P5, June 2, 2025)

Similar to P4's observation on facial datasets as nonverbal data, P5's account reveals the complexity involved in adopting and managing voice intonation datasets as verbal data. In line with this, P6 elaborated that all datasets—both verbal and nonverbal—must be embedded into an AI-based application adopting a convolutional neural network (CNN) architecture for visual analysis, and a recurrent neural network (RNN) for sequential data such as speech.

"CNN excels at reading images and videos, while RNN is better suited for audio and temporal sequences. When you combine them, the system will better understand context, rather than just isolated bits of information." (P6, June 18, 2025)

This statement highlights the distinct functional domains of CNN and RNN. Consequently, for an automated evaluation system to process both nonverbal and verbal data effectively, both architectures must be implemented in tandem. P9 stressed the importance of integrating CNN and RNN through proper coding; without a solid connection, the analysis results risk overlapping or misinterpretation.

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> *"The key is integration. CNN and RNN are like two eyes and two ears. If they're not connected, the results will overlap or be misinterpreted." (P9, July 4, 2025)*

This suggests that professional coding expertise is essential to ensure connectivity and prevent errors in identification and interpretation. P8, the most experienced among the AI practitioner participants, then described how the system would operate procedurally. The process involves identifying facial expressions, identifying voice intonations, categorizing these according to the dataset, and interpreting the categorized results.

> *"So the application must have both CNN and RNN. Then the verbal and nonverbal datasets need to be input. Next comes coding and training the AI so that CNN and RNN performance is connected to the dataset and can classify the analysis results according to the categories we set. CNN analyzes video, and RNN analyzes voice intonation. For example, if the expression is enthusiastic and the intonation is confident, that can be categorized as a positive performance. But remember, the application's function must first be tested. The analysis results should also be validated by humans." (P8, July 19, 2025)*

P8's explanation made a substantial contribution to the connectivity of the ideas presented, indirectly validating the points made by P6 and P4, while clearly illustrating the interrelation between datasets, CNN, and RNN systems, and their integration. His cautionary note—"the application's function must first be tested"—along with his insistence on human validation, indicates that the automated microteaching evaluator is positioned as a predictive assessment tool. This predictive nature was also affirmed by P5, who remarked: "The evaluation results will be predictive in nature." (P5, July 27, 2025)

Beyond the operational sequence, P7—who has handled multiple cross-cultural AI projects—reminded the team of a frequently overlooked challenge in developing such applications:

> *"Gathering a quality dataset is expensive, especially if you want it to be valid across multiple cultural contexts. The challenge is not only cost differences in communication styles across cultures can cause the system to misinterpret. Not to mention, AI still struggles when the knowledge being tested is abstract or conceptual." (P7, July 30, 2025)*

P7's remarks point to the dual challenge of cultural variability in communication styles and the high cost of developing high-quality datasets—an observation shaped by his view of higher education in Indonesia, where financial constraints are common.

In summary, these practitioners agreed that the automated microteaching evaluator system must be developed in gradual stages: starting with the collection of representative verbal and nonverbal datasets, training CNN and RNN systems, integrating them through programming, and conducting field trials with human validation.

4.3. Synthesis of Findings

The analysis reveals that the two participant categories exhibit complementary orientations. The academic experts contribute domain knowledge regarding the learning process, the imperative for microteaching evaluation to undergo technological renewal, and the core values that must be preserved in teacher education. Their focus rests on the quality objectives of teacher education assessment: objective, efficient, data-driven, and aligned with contemporary developments. In contrast, the AI practitioner category offers the technical know-how required to construct such a system, ranging from dataset architecture and algorithm selection to strategies for multimodal integration. They also highlight the technical and financial constraints that could potentially hinder implementation. Based on the in-depth interviews and thematic analysis of emerging ideas and sub-ideas, a synthesis of the research findings is presented in Figure 1.

Figure 1. Mind Map of Findings

As illustrated in Figure 1, when these two perspectives are combined, a conceptual framework emerges for developing an automated microteaching evaluator. The academic experts ensure that the system retains pedagogical relevance, while the AI practitioners safeguard its technical functionality and feasibility. Both agree that although technology can process data rapidly and consistently, human judgment remains essential at certain stages to ensure accuracy and context sensitivity. Thus, automating microteaching evaluation is not merely a technological project but a cross-disciplinary endeavor that demands synergy between pedagogy and AI. If implemented with careful planning, such a system could become a significant milestone in teacher education reform in Indonesia and, more broadly, be adopted by teacher education programs in other developing countries worldwide.

5. Discussion

This study sought to explain how an AI-based application automates the microteaching evaluation process. The findings illustrate a systematic eight-stage workflow integrating convolutional neural network (CNN) and recurrent neural network (RNN) architectures for multimodal analysis. This configuration provides an operational model that demonstrates how automation functions in practice within teacher training contexts. Following the synthesis of research findings presented in the previous section, we conducted a rigorous re-sorting of the data to identify the most relevant data to address the primary research question: "How does automation work in microteaching evaluation by an AI-based application through video analysis?" In connection with the systematic explanation of the stages, once the sorting process was completed, the steps were arranged and reviewed repeatedly until no misperceptions were detected. Please see Figure 2.

Figure 2. Automate The Microteaching Evaluation Through Video Analysis By An AI-Based Application

In Figure 2, the automation of microteaching evaluation through video analysis by an AI-based application is described as a sequence comprising eight stages. 1) Get the dataset of human face expressions as a non-verbal symbol. 2) Get the dataset of human voice intonation as a verbal symbol. 3) Put the dataset into the AI-based application. 4) Adopted the convolutional neural network (CNN) system for video analysis. 5) Adopted the recurrent neural network (RNN) system for voice analysis. 6) Coding the connection of CNN & RNN to the dataset. 7) Identify facial expression & voice intonation, categorize & interpret based on the dataset.

These findings are consistent with earlier studies that examined AI-assisted feedback in microteaching. For instance, Truong et al. (2025)and Mu et al. (2025) found that AI can enhance pre-service teachers' reflection and instructional confidence by providing real-time feedback. However, their models positioned AI as a supportive assistant rather than an autonomous evaluator. In contrast, the present study advances the field by demonstrating a fully automated evaluation system, in which AI independently processes and interprets both visual and auditory cues to generate pedagogical insights.

These findings align with broader trends in multimodal learning analytics, as mapped by Ouhaichi et al. (2023), where researchers integrate diverse data sources (e.g., video, audio, gesture) to enrich the interpretation of learning processes. While many prior studies treat modalities independently, our system's synergy of CNN and RNN aims to fuse them into a unified evaluation pipeline.

In addition, Zhang et al. (2025) demonstrate how multimodal analytics can support evidence-based evaluation in collaborative programming environments, combining visual and interaction data for performance judgment. Although the domain differs (programming vs. teaching), the principle of multimodal fusion underscores the novelty of our work in applying similar integrative logic to microteaching evaluation.

These eight stages answer the research question and extend beyond existing frameworks in the literature. The datasets of human facial expressions and voice intonations embedded in the AI-based application serve as the foundation or "reference" for the automation of evaluation. When the AI-based application identifies students' facial expressions during instruction through the convolutional neural network (CNN) system, or identifies students' voice intonations during learning through the recurrent neural network (RNN) system, the identification results of both will be categorized based on the pre-embedded datasets of human facial expressions and voice intonations.

The findings of this study outline a workflow for the automation of microteaching evaluation entirely supported by AI, with eight systematic stages that integrate CNN-based video analysis for facial expressions and RNN-based audio analysis for voice intonations. The carefully curated datasets of facial expressions and voice intonations become the primary benchmarks in the evaluation process, enabling the AI system to interpret non-verbal and verbal indicators in an integrated manner. These stages represent a computational workflow that is not merely mechanical, but also epistemological, as the data structures, algorithms, and categorization processes are designed to emulate how human evaluators assess the quality of microteaching performance.

The uniqueness of the workflow, extracted from the perspectives of learning experts and AI practitioners, lies in the integration (coding) stage between CNN and RNN, which becomes a synergistic node of two distinct analytical domains—visual and audio. This integration facilitates multidimensional evaluation that does not rely solely on a single communication modality. Consequently, the analysis results not only produce quantitative scores but also yield contextual interpretations of teaching quality, encompassing dimensions such as expressiveness, vocal clarity, and the coherence between the two. This approach projects strong potential for application in teacher training that is more precise, consistent, and free from the vulnerabilities of subjectivity.

The present findings resonate with prior research emphasizing AI's role in supporting microteaching reflection and performance enhancement (Mu et al., 2025; Truong et al., 2025). Similar to these studies, the current research identifies AI as instrumental in strengthening pre-service teachers' instructional quality through data-driven feedback mechanisms. However, unlike previous models that positioned AI as an assistive tool or tutor, the present study extends the concept by positioning AI as an autonomous evaluator, capable of independently interpreting multimodal inputs of facial and vocal expressions.

Upon deeper examination, the principal strengths of these findings lie in three fundamental aspects.

1. Analytical Precision. The combination of CNN and RNN in microteaching evaluation optimizes the system's ability to capture micro-level details—both in the visual domain (e.g., eyebrow movements, eye contact, micro-expressions) and the audio domain (intonation, pacing, and vocal emphasis). This enables a far more granular measurement compared to manual evaluations reliant on the subjective perception of assessors.

2. Assessment Consistency. An application built on such a system has the capacity to reproduce evaluations consistently, thereby reducing inter-rater variability, which often poses a challenge in pedagogical assessment (Memarian & Doleck, 2024; Swiecki et al., 2022).

3. Potential for Cross-Context Generalization. Given its modular datasets, the system can be adapted to diverse languages, cultures, and teaching styles. With the addition of new datasets, the algorithm can adjust its interpretations to the non-verbal and verbal communication norms across different educational contexts worldwide (Martínez-Comesaña et al., 2023).

As a result of these three strengths, the significance of this research has the potential to influence two major domains. First, it can enhance the quality of teacher training in the era of Education 5.0 through evidence-based evaluation. Second, it can establish an automated feedback loop that

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accelerates the learning curve for pre-service teachers, as emphasized by (Konakbayeva et al., 2025) and (Mu et al., 2025).

These findings align with the concept of AI-assisted microteaching proposed by Konakbayeva et al. (2025), in which AI plays a role in enhancing pre-service teachers' confidence and instructional quality—although their study positions AI as a teaching assistant in microteaching, rather than as an evaluator of microteaching implementation, as in the present study. The interpretive output of the automated microteaching evaluation in this study, which serves as automated feedback for educational leaders, is consistent with the automated feedback described by Mu et al. (2025). In their study, they also emphasize automated feedback as an element capable of strengthening pre-service teachers' non-verbal teaching skills, which is congruent with the present research's focus on facial expression analysis.

From a methodological perspective, this approach overlaps with pattern recognition design in intelligent evaluation systems, as advanced by Tang et al. (2023), where multimodal analysis broadens the accuracy of microteaching skills measurement. Previous studies, such as (Saralar-Aras & Güneş, 2024) and (Azrai et al., 2020), highlight microteaching as a platform for teacher training, with their focus tending towards the integration of peer assessment and distance learning. By contrast, this study positions AI as the primary evaluator that autonomously conducts analysis and categorization, rather than functioning merely as a training aid.

The most notable novelty of this research lies in the direct integration of CNN and RNN into a single automated evaluation workflow. Rather than functioning separately, the integration of CNN and RNN described here embodies strong cohesion—each is configured to complement and reinforce the other, producing a more holistic pedagogical interpretation. Such an approach has not been explicitly detailed in the literature, including in works such as (Winkler-Schwartz et al., 2019) applying machine learning to assess surgical skills in virtual reality, which relied predominantly on a single modality. Furthermore, the original contribution of this study is the formulation of a clear eight-stage operational blueprint—as illustrated in Figure 2—making it more replicable and positioning it as a potential standard framework for AI-based teaching evaluation research and development.

Despite its methodological novelty, several limitations must be acknowledged. The reliability of automated interpretation remains contingent on the diversity of datasets, particularly in capturing cultural variations in facial expressions and vocal intonations. This challenge is consistent with the ethical concerns raised by Handelman et al. (2019) and Maras and Alexandrou (2019), who highlight the need for transparency and fairness in AI-driven assessments. Moreover, as noted by Joshi et al. (2021) and Swiecki et al. (2022), users' digital competence and data privacy must be safeguarded through adequate human oversight and institutional capacity-building.

Practically, this study provides educators and policymakers with a scalable framework for AI-based microteaching evaluation that minimizes human bias while enhancing feedback accuracy. Future research should expand the multimodal datasets across different cultural and linguistic contexts to improve generalizability and ethical robustness.

Nevertheless, the reliability of this automated evaluation faces challenges, particularly in relation to the variability of meaning in voice intonation, which often carries different intentions across diverse cross-cultural communication styles. Therefore, for use with participants from varied cultural backgrounds, a more extensive voice intonation dataset is required. On the other hand, AI-based automated microteaching video assessment also faces significant challenges related to transparency in evaluation processes, data privacy, potential inequities in technological access (Handelman et al., 2019; Maras & Alexandrou, 2019), and users' digital competence (Joshi et al., 2021; Swiecki et al., 2022). Accordingly, the automated microteaching evaluation results presented in this study must remain under the control of, and be acted upon ethically by, professional educational leaders—

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always grounded in pedagogical and ethical reflection—as similarly recommended by (Swiecki et al., 2022) and (Memarian & Doleck, 2024). To mitigate shortcomings in users' digital competence, such implementation must be supported by adequate human resource capacity and sufficient technological infrastructure.

6. Conclusion

This study directly answered the research question about how the AI-based application automates the microteaching evaluation process by extracting and structuring its operational mechanism into a clear eight-stage workflow. The findings show that automation occurs through an integrated system that combines convolutional neural networks (CNN) for visual analysis and recurrent neural networks (RNN) for audio interpretation. The interaction between these two neural architectures enables the system to identify, categorize, and interpret multimodal cues such as facial expressions and voice intonations. Through this process, the system replicates the reasoning patterns of human evaluators within an objective and consistent computational framework.

By formulating this operational blueprint, the study achieved its main objective, which was to conceptualize and validate a replicable model for AI-based automated evaluation in microteaching. This model demonstrates the technical feasibility of AI-driven performance assessment and contributes methodologically to the growing field of multimodal learning analytics. It offers a foundation for future educational AI applications that are both data-informed and pedagogically grounded.

The findings also highlight practical implications. Automated evaluation has the potential to enhance consistency, scalability, and transparency in teacher education by reducing inter-rater subjectivity and by providing structured feedback loops for pre-service teacher development. However, several challenges remain, particularly those related to variations in the meaning of voice intonation across different cultural contexts, concerns about data privacy, and the substantial financial investment required to implement AI infrastructure in educational institutions.

To strengthen the reliability and ethical robustness of such systems, future studies should employ quasi-experimental and cross-cultural validation methods. Expanding datasets to reflect diverse linguistic and cultural contexts will ensure greater inclusivity and fairness in automated evaluation. Overall, this study establishes both an operational and conceptual foundation for advancing AI-assisted microteaching evaluation and transforms the assessment process into a transparent, data-driven, and pedagogically intelligent system.

7. Suggestion

Based on our findings, these results recommend creating an application that can automate microteaching through the eight stages that we have identified. This recommendation is linked to the limitation of this result, which explores the theoretical explanation without direct practice. It is important to enhance the efficiency of microteaching evaluation and promote the smart utilization of AI in teacher education.

Declarations

Author Contributions. N.H.: conceptualization, methodology, visualization, editing of original manuscript preparation. E.P.: writing original manuscript, methodology. Y. R.: data collection, resources. E.H.: data analysis. N.: investigation. D.N.: methodology. S.D.: validation. S.J.: review. All authors have approved the final version for publication of this article.

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