BÖLÜM 21

NÜKLEER TIP PRATİĞİNDE YAPAY ZEKA UYGULAMALARI

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Giriş

Yapay zeka, bilgisayar sistemlerinin insanların akılcı davranışlarını taklit ederek problem çözmeye yönelik oluşturulan sistemlerdir. Yapay zekanın temel amacı, bilgisayar sistemlerini insanların düşünme biçimine benzeyen şekilde programlamak veya eğitmek suretiyle insan benzeri zekayı simüle etmektir. Bu amaçla, birçok farklı yöntem ve teknik kullanılır. Bunlar arasında makine öğrenimi, derin öğrenme, doğal dil işleme, uzman sistemler, genetik algoritmalar, bilgi temsili ve mantıksal çıkarım gibi teknikler yer alır. Son zamanlarda birçok alanda kullanımının arttığı gibi tıp ve sağlık alanında da yapay zeka uygulamaları gündeme gelmiştir ve halen gelişmekte olan bir alandır. Bilgi teknolojisinin gelişimi ve hesaplamanın gücü, klinik ve teşhis kararları için yapay zekaya dayalı teknolojinin uygulanmasına ve prosedürlerin otomasyonuna izin vererek uzmanların doğrudan iş yükünün azalmasına yol açabilmektedir.

Makine öğrenimi, yapay zekanın bir alt grubu ve temel taşlarından biridir. Bir bilgisayar sisteminin verilerden öğrenerek, deneyim kazanmasını ve kararlar almasını sağlar. Açık programlama olmadan bu görevleri gerçekleştirebilen bilgisayar algoritmaları olarak kabul edilebilir. Veri analizine dayanarak deneyim kazanması ve otomatik olarak öğrenme yapabilmesini sağlayan bir yapay zeka dalıdır (1). Makine öğrenmesi, programlanmış talimatlar yerine veriye dayalı olarak örüntüleri ve ilişkileri keşfetmeyi hedefler. Bu şekilde, sistemin gelecekteki verilere dayanarak tahminler yapması, desenleri tanıması ve kararlar alması mümkün olur. Derin öğrenme ise büyük veri setlerinden öğrenme yapabilen ve karmaşık yapıları tanıyabilen yapay sinir ağlarına dayalı bir makine öğrenimi alt dalıdır (1). Bu yöntemde, sinir ağı modeli, eğitim veri setine dayalı olarak ağırlıkları ayarlayarak, verilerin içerdiği örüntüleri ve ilişkileri otomatik olarak öğrenir. Derin öğrenme, özellikle büyük veri setleri ve karmaşık problemlerle ilgilenen alanlarda büyük başarılar elde etmiştir. Genellikle büyük hesaplama gücü gerektiren ve büyük miktarda etiketli veriye ihtiyaç duyan karmaşık yapılar olduğundan, eğitim ve uygulama süreçleri zaman alabilir. Ancak, derin öğrenme alanındaki araştırmalar ve gelişmeler hızla devam etmektedir.

Nükleer tıp alanında bu teknolojiler, görüntülerin yorumlanması, hastaların sınıflandırılması, radyomik kavramlarla entegrasyon, otomatik segmentasyon, risk tahminleri ve hatta görüntüyü terapötik sonuçlarla veya hayatta kalmayla ilişkilendirmenin otomasyonunu sağlar (2). Bu görevlerin birçoğunun otomasyonu, iş akışını ve yönetimi iyileştirerek, kalitede küresel bir gelişme sağlaya-

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ve yeniliklerle nükleer tıpta ve uygulamalarında önemli bir gelişmeyi temsil edecek yapay zekaya dayalı araçları anlamak, uygulamak, geliştirmek, test etmek ve kullanmak için çalışmamız gerektiği açıktır. Sonuç olarak, klasik görüntü alma ve yorumlama yönteminde ve bunların klinik iş akışına entegrasyonunda devrim yaratabilecek heyecan verici bir sürecin başlangıcındayız.

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