Bölüm 6

ÜROLOJİ VE YAPAY ZEKÂ

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GİRİŞ

Yapay zekâ (YZ) terimi ilk olarak 1956'da John McCarthy tarafından kullanılmıştır. Daha sonra Alan Turing, insanı taklit etme ve karar verme yeteneği olan bir bilgisayar makinesi tanıtmıştır (1). Yapay zekânın atılımı, 2012 ImageNet yarışmasında derin evrişimli sinir ağının (ESA) nesneleri algılama ve görüntüleri sınıflandırmadaki son derece hassas performansından sonra gerçekleşmiştir (2).

1. YAPAY ZEKÂ NEDİR?

'Yapay zekâ' terimi genellikle düşünme, öğrenme ve problem çözme gibi insan bilişsel işlevlerini taklit ederek karmaşık kalıpları analiz eden veya karmaşık sorunları çözen bir teknolojiyi ifade eder (3). Yapay zekâ teknikleri, istatistiksel dağılımlara dayalı varsayımlar yapmadan mevcut verilerden öğrenmeyi içerir ve yeni veriler üzerinde tahminlerde bulunarak daha iyi kararlar almayı sağlar (şekil-1) (4).

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Ürolojik hastalıklarda YZ uygulaması üzerine yapılan çalışmaların çoğunda birkaç sınırlama vardır. İlk olarak, çalışmaların tasarımında farklılık olduğundan karşılaştırılması zordur. İkinci olarak, çoğu çalışma algoritmaları kendi veri kümeleri içinde doğrulanmıştır; Bu nedenle bu çalışmalar, dış doğrulamadan yoksundur ve sonuçları diğer veri kümelerinde genelleştirmek zordur.

Gelecekteki çalışmalar, daha büyük tıbbi veritabanları oluşturmaya ve YZ tekniklerini daha da genişletmeye odaklanacaktır. Gelişmiş algoritmaların kullanımı akıllı telefonlarda gerçekleşebilir veya internet üzerinden erişilebilir hale gelebilir. Makine teşhisinin güvenilirliği ile ilgili sorunlar mevcuttur ancak bu önyargılar teşhiste engel oluşturmayacaktır.

Sonuç olarak, yakın gelecekte YZ uygulamaları kılavuzlarda yerlerini bulacakları ve karar verme sürecinde devrim yaratacakları için klinik uygulamalarda değişiklikler görebiliriz. Bununla birlikte, zekâ, uyum ve görev duygusunun insan nitelikleri, YZ'nin daha da geliştirilmesinde önemli faktörler olacaktır.

Dünya Ekonomik Forumu Başkanı Klaus Schwabe, birkaç yıl önce şu açıklamaları yapmıştır: "Yaşama, çalışma ve birbirimizle ilişki kurma şeklimizi temelden değiştirecek bir teknolojik devrimin eşiğindeyiz. Bu dönüşüm; ölçeği, kapsamı ve karmaşıklığıyla, insan türünün daha önce deneyimlediği hiçbir şeye benzemeyecek." (113)

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